Section 3

SECONDARY DATA ANALYSIS OF VISIBILITY EFFECTS

3.1 OVERVIEW of SECTION 3

Section 3 is a related group of studies of the role of visual air quality in particular household activities. Swimming, Hancock Tower visitation, and baseball attendance represent active and passive outdoor recreation. Studies of view-oriented residences explore the relationship between view and visual air quality at the household residence. Auto and air traffic studies investigate the importance of visual air quality in basically non-recreational outdoor activities. Finally, the study of TV viewing establishes the role of visual air quality in influencing the choice between indoor and outdoor recreation.

These studies complement the contigent valuation work of Section 2 in several ways. First of all, the studies of Section 3 all pertain to particular markets, such as baseball attendance or TV viewing, whereas contingent valuation estimates total visibility value irrespective of the uses to which they are put. In each case the individual market studies demonstrated that people reveal an implicit willingness to pay for visibility improvement. Ideally, aggregate visibility benefits would be determined by both methods and compared in order to validate the results. While this is not feasible, nevertheless a judgment can be made concerning the plausability of the partial comparison that is possible.

Secondly, the value of visiblity improvements in these papers are estimated from historical records of completed activities. For example, the value of a one mile average improvement in visual range is estimated to be worth about 3 cents per person in attendance, including approximately 10,000 additional persons who would attend under the better visibility conditions. This result is derived from recorded time series information on attendance along with visibility and a number of other variables that effect attendance. People reveal the dollar value of their preference for visibility by their behavior in the face of actual visibility change .

Thirdly, the underlying theory of visibility valuation is the same for the market studies of Section 3 and the CV work of Section 2. The modeling and empirical estimation are quite different. Nevertheless, the common theoretical basis makes the two empirical approaches complimentary. Evidence that results are consistent strengthens our confidence in the results as well as the methods that have been developed to obtain them. The Hancock Tower study in 3.3 provides important directly comparable evidence concerning the two empirical approaches. The conclusion is that the hypothesis of a statistically significant difference between them is rejected.

3.2 OUTDOOOR RECREATION

3.2.1 Swimming

Swimming is one of the major summertime recreational activities available in the Chicago metropolitan area. With numerous beaches and over one hundred pools, the Chicago Park District alone has an annual attendance of many millions. Unfortunately for this analysis, admission to Chicago facilities is without charge, and no accurate records are kept of attendance as a result. Data for both beach and pool attendance were provided by the Wilmette Park District, which operates one of each type of facility just north of Chicago.

Visibility affects the demand for swimming in at least three ways. Consider the simple utility function:

$$U_P = U(H,Q,C,T) \ ,$$

where U_P is the utility generated by a pool visit, H is the perceived health benefits from swimming, Q is a measure of environmental quality, C is the level of thermal discomfort faced during the day, and T is the time spent at the pool. It is clear that all of these parameters are interrelated to some extent. For example, a hot day may cause an increase in photochemical smog, which may induce an individual to spend less time outdoors due to the decreased health benefits as perceived by the individual. The simple function is useful because it illustrates the mechanisms by which visibility may enter into the demand equation. The first of these mechanisms is the "pure-visibility" effect, and represents the amenity value of visibility in determining the overall utility generated simply by enjoying a nice day. The second is the "indicator" effect, which reflects the use made by individuals of visibility as an indicator of the presence of unhealthy air-pollutants. The indicator effect may be quite important in the Chicago area, as the public receives many warnings in the summer to avoid physical activity during periods of high ozone levels. These warnings may come to be associated with days in which visibility is poor, so that poor visibility may deter swimming for health reasons, even if the poor visibility is caused by harmless natural conditions.

The third way visibility enters the demand equation is through its effect on the transmission of ultraviolet radiation, which is responsible for tanning (and burning) the skin. Since many swimmers spend a great deal of time and money to get a tan (i.e., special lotions, etc.), any decrease in the ability to get a tan represents a real loss in utility.

To identify these effects from raw attendance figures requires an accurate treatment of thermal comfort. A precise, absolute definition of comfort is not possible, as it is a subjective evaluation which differs greatly among individuals. Auliciems (1) showed that four factors influence human comfort, that is, the proportion of individuals who respond negatively to the question, "Are you comfortable?". These four factors are temperature, humidity, air movement, and thermal radiation, such as the infrared radiation from the sun. These factors interact with each other to yield a level of comfort: which is particular to the individual. The National Weather Service reports two indices which attempt to integrate these factors into a more useful measure than simply using temperature. These are the temperature-humidity index (THI) and the wind-chill index (WCI). Neither is particularly suited to this analysis for several reasons. The THI neglects the effect of the wind, since it was developed primarily to monitor factory conditions, and it does not respond to human comfort in a linear way. A THI reading of 65 implies that everybody is comfortable, while a reading of 70 corresponds to discomfort in 10% of the population, 75 corresponds to 50%, and 80 to virtually 100% discomfort. The WCI does not take into account humidity, as this factor is almost always negligible when compared to the wind effect outdoors in the winter. Also, the published formulas are inappropriate because they assume a normal amount of skin exposure and moisture, while in swimming the entire body is wet with most of the skin exposed to the wind. To account for temperature, humidity, and wind, a set of interaction terms is included in the regression, as well as the terms' independent effects. The fourth comfort-related factor, radiant energy, is assumed to be a simple linear function of cloud cover and visibility.

It is important to keep in mind that the true marginal decision variable is how much time to spend at the pool, or in the aggregate, how many person-hours are spent, and not how many people attend in a day, which is what we have data for here. At best, we can make some crude assumptions about average time spent at the pool and the average value of time of those who attend. Even so, it is questionable whether any reasonably accurate dollar value can be assigned to visibility in this particular case. What can be established, however, is the extent to which visibility plays a role, consciously or not, in the consumption decision of individuals. A decrease in attendance due to reduced visibility implies a decreased opportunity set and a reduction in utility to those who no longer attend as well as those who continue to attend. Assigning a dollar value based entirely on the reduction in attendance may also prove unsound due to the substitution into other, less visibility-elastic activities or even into more work and less leisure as the quality of leisure time is decreased.

3.2.1.1 Empirical Model

Two models are estimated using Wilmette data and surface weather observations at O'Hare Airport for the years 1977-1979. Swimming data are also available for

1980, and are used for prediction-verification. Due to the lack of data on certain important variables, such as wave height, water temperature, and pollution levels in the lake, the beach data are not used in this analysis. Rather, the emphasis is placed on the pool, which is a controlled environment not subject to closing unrelated to the weather.

The first model to be estimated assumes a simple, readily interpretable linear relationship. The relationship is of the form

$$P = \alpha + \beta_1 V \sum_{i=2}^{n} \beta \chi \quad ,$$

where P is daily pool attendance, V is visibility, and χ_i are other factors which effect attendance. Unbiased estimates could be achieved for the estimated parameters by taking first differences of all the variables, 364 days apart. However, with the limited dataset and the subtle quality of the effects being measured, first-differencing is highly undesireable. To account for purely temporal effects, a comprehensive set of dummy variables and functions are employed on a portion of the data, the results of which are compared with those obtained using first differences. In addition, the data are analyzed for each year separately in addition to the pooled regression to check for structural stability between years. Data for the year 1980 are included as an additional check on the parameter estimates.

A simple plot of attendance by date indicates a tendency for the attendance to fall in clusters. It is determined whether this is due to a simple clustering of days similar meteorologically, or whether there is a lagged relation among the data. The disturbances are examined for autocorrelation to see whether General Least Squares methods would be more appropriate than OLS estimators.

In addition to the linear model, a second model is used, of the form.

$$LOG(P) = \alpha + \sum_{i=1}^{n} \beta_i LOG(\chi_i) + \sum_{i=n+1}^{m} \beta_i \chi_i \quad ,$$

where the χ_i are expressed in log form, if continuous, or else left in levels if the relationship is best described by an exponential function, or if the variables are discrete. This model has the advantage that elasticities are estimated directly, but is not as straightforward and simple as the linear model.

3.2.1.2 Regression Results

Ta. 3-1 shows the results of the first regression model. The important points which led to this final regression are:

1. Day-of-week effects were minimal and not statistically significant. This includes a simple weekend/weekday dummy variable, which was also tried.
2. The linear model is not structurally stable. The values for the coefficients differ significantly for each of the three years in question. (F-ratio of 3.978. Separate year results are not reported here.) The pooled regression using all three years can be looked at as an “average” representation of the effects.
3. Lagged exogenous variables were not statistically significant, though their signs and relative magnitudes were as expected. In addition, the data showed no significant autocorrelation, using the Durbin-Watson method.

TABLE 3-1
Pool Attendance: Model 1

VARIABLE (units)	PARAMETER ESTIMATE	STANDARD ERROR	T-RATIO	PROB > T
INTERCEPT	464633.7	350765.7	1.3246	0.1867
RAIN (% of Day)	-1.061104	2.273052	-0.4668	0.3206 *
FOG (% of Day)	-0.051259	2.489467	-0.0206	0.4618 *
TEMP (°F)	543.921259	164.347770	3.3096	0.0006 *
WIND (MPH/10)	-292.932312	117.645255	-2.4900	0.0068 *
HUMIDITY (%)	57.678240	39.192380	1.4717	0.0713 *
CLOUD-COVER (%)	-4.782367	1.209490	-3.9540	0.0001 *
VISIBILITY (Mi./10)	1.852527	0.853752	2.1699	0.0156 *
$\sqrt{\text{WIND}}$	6511.505	2526.044	2.5777	0.0068
TEMP-WIND **	3.943894	1.500730	2.6280	0.0092
TEMP-$\sqrt{\text{WIND}}$ **	-84.489434	32.034411	-2 . 6375	0.0089
HUMIDITY-WIND **	-0.192682	0.066548	-2.8954	0.0042
TEMP.-HUMIDITY **	-0.434404	0.494560	-0.8784	0.3807
COS(T) ***	3364.711	1648.974	2.0405	0.0425
SIN (T) ***	-3488.21	2921.867	-1.1938	0.2338
TTREND ***	-78,873748	54.698816	-1.4420	0.1507

* One-tailed test
** Comfort - Interaction Terms
*** Time-Effect Terms

SSE	32258740	F-Ratio	25.51
Deg. of Freedom	220	Prob> F	0.0001
MSE	146630.6	R-Square	0.6349

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The results of the final regression can be summarized thus:

1. Rain and fog effects are not well accounted for in a linear model. This is perhaps due to the discrete nature of these variables as they exist in our data set.
2. The model accounts extremely well for comfort-related effects, both independent and interaction terms are significant with the proper signs.
3. Visibility has a significant effect on attendance. The effect is not stable between years, but ranges between 1.24 and 3.73 persons per tenth-of-a-mile increase in visibility. When the data are pooled, an estimate of 1.85 is arrived at. The high of 3.73 was achieved in 1979, the year the model best fit the data.

The second model which was estimated was the log-log relationship. On the whole, this model was a disappointment, as some of the variables' effects were masked, or were not well accounted for in multiplicative relationships. Results from this regression are listed in Ta. 3-2.

While the log-log relationship expressed rain and fog effects in exponential form, which was found most appropriate, it seems to have been an inappropriate functional form for other variables. Temperature and wind have the anticipated effects, but cloud cover, humidity, and visibility have no significant effect. This model also has less overall explanatory power than the linear model ($R^2 = .5717$), and so the conclusions for this investigation rely heavily on the first model.

TABLE 3-2

Pool Attendance (Log): Model 2

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T-RATIO	PROB>T	
INTERCEPT	1338.153	10907.83	0.1227	0.9025	
RAIN	-0.040805	0.007502444	-5.4389	0.0001	*
FOG	-0.021650	0.008816437	-2.4556	0.0074	*
LOG(TEMP)	15.991371	1.486479	10.7579	0.0001	*
LOG(HUMIDITY)	-0.561598	0.594286	-0.9450	0.1728	*
LOG(WIND)	-0.663739	0.293846	-2.2588	0.0125	*
LOG(CLOUD-COV.)	-0.00686768	0.051006	-0.1346	0.4465	*
LOG(VISIBILITY)	0.025559	0.252146	0.1014	0.4597	*
LOG(TTREND)	-158.950272	1244.464	-0.1277	0.8985	
COS(T)	3.453727	5.731853	0.6025	0.5474	
SIN(T)	0.203768	10.422159	0.0196	0.9844	

* One-Tailed Test

SSE	435.025664	F-RATIO	30.04
DEG. OF FREEDOM	225	PROB> F	0.0101
MSE	1.933447	R-SQUARE	0.5717

3.2.1.3 Conclusions

1. An increase in ambient visibility levels of one mile will increase attendance from three to five percent. This represents an annual increase in attendance of between 1728 and 2880 persons.
2. The lack of day-of-week effects suggests a population consisting mainly of children and younger adults with a correspondingly low employment rate. Since environmental amenities are usually income-elastic, this would tend to yield a site-specific estimate which was below the average valuation over the entire population.
3. A large portion of the variation remains unexplained in the models used here. There is likely a large random element, due to reasons cited in number 1 above, but in addition, it appears that the inter-relation between the variables is a rather complex function, which can only be approximated by a linear relationship.

The remainder of the chapter presents the results of an investigation into the effects of visibility on common recreational and other activities. For the most part, we examine activities for which the relevant demand elasticities are unknown, and so benefit estimates of visibility changes are not possible. However, in the case of major league baseball attendance, estimates of demand elasticities have been made, for example, by Noll and Demmert.

General models of activity choice with visibility as an input into household production functions have already been presented in this report. For this reason, none are presented here. Instead, regression models are introduced, and the variables described. Following each are the results of one or more regression analysis with a brief discussion of the results. All of the activities measured were in the Chicago Metropolitan Area.

3.2.2 Television Viewing

With the aid of A.C. Nielsen's "Nielsen Television Index"* a dataset consisting of the total number of households using television at the hours of 1:00 P.M., 2:00 P.M., and 3:00 P.M., for each day during calendar years 1978 and 1979 was assembled. In addition, the number of households watching Chicago Cubs home games was determined. Due to the lack of lights at the stadium, all games take place between noon and around 4:00 P.M. These data are useful in the discussion of baseball attendance below.

Many factors undoubtably influence the number of television viewers. One for which we have little independent data is program quality. The choice of the early afternoon hours is partly an attempt to control for program quality, as there are relatively few changes in scheduling in this time period. Also, it enabled the comparison of the game and non-game days of the Cubs, as described above.

To examine the influence of visibility on television audiences, we separated its effects from other meteorological and temporal factors. The regression results are given in Ta. 3-3. The intercept, 31.86, represented an average Wednesday in May, meaning 31.86% of the 3 million households watching T.V. The effect of visibility is given by the two variables VIS15 and WKNDVIS. The effects of a one mile increase in visibility, assuming

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* Thanks are due to Maureen Gorman of NTI for her kind assistance in providing these data.

TABLE 3-3

Percent of Households Using Television, 1978-79

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T RATIO	PROB>|T|
INTERCEPT	1	31.862665	1.407201	22.6426	0.0001
RA15	1	0.019619	0.005993813	3.2732	0.0011
SN15	1	-0.00618701	0.007097675	-0.8717	0.3837
WIN15	1	0.008701367	0.003107462	2.8002	0.0053
TCL15	1	0.016687	0.00402075	4.1501	0.0001
VIS15	1	-0.013373	0.003915276	-3.4157	0.0007
TEM15	1	-0.081347	0.014113	-5.7641	0.0001
FOOTBLSA	1	1.617240	0.764520	2.1154	0.0348
FOOTBLSU	1	6.678667	0.763180	8.7511	0.0001
FTBLHOL	1	5.454071	1.765358	3.0895	0.0021
CUBHOME	1	2.562305	0.534686	4.7922	0.0001
CUBAWAY	1	0.716211	0.530855	1.3492	0.1777
BLIZZARD	1	5.241333	1.123943	4.6633	0.0001
M	1	0.918224	0.471162	1.9489	0.0517
T	1	-0.320498	0.465496	-0.6885	0.4914
R	1	-0.073249	0.470864	-0.1556	0.8764
F	1	-0.283101	0.467240	-0.6059	0.5448
S	1	6.847284	1.241751	5.5142	0.0001
SU	1	12.259061	1.247545	9.8265	0.0001
M1	1	4.850261	1.004174	4.8301	0.0001
M2	1	2.067644	0.952657	2.1704	0.0303
M3	1	2.955393	0.806152	3.6660	0.0003
M4	1	1.445582	0.639560	2.2603	0.0241
M6	1	1.800524	0.620328	2.9025	0.0038
M7	1	2.639546	0.628826	4.1976	0.0001
M8	1	3.760193	0.627449	5.9928	0.0001
M9	1	2.744425	0.645459	4.2519	0.0001
M10	1	3.327091	0.739155	4.5012	0.0001
M11	1	2.894163	0.792583	3.6516	0.0003
M12	1	3.107789	0.854282	3.6379	0.0003
WKNDVIS	1	-0.00134655	0.007019629	-0.1918	0.8479
WKNDTEM	1	-0.104334	0.012805	-8.1482	0.0001
WKNDRA	1	0.017010	0.014474	1.1752	0.2403
WKNDSN	1	0.015358	0.015645	0.9817	0.3266

SSE	7584.145	F RATIO	49.41
DFE	689	PROB>F	0.0001
MSE	11.007467	R-SQUARE	0.7030

Source: A. C. Nielsen Co.

local linearity, is -.0134, meaning .134% of the 3 million households stop watching T.V. or around 4,000 households. The effect if that increase happens on a weekend is a further reduction of 400 households. The prime effect is very well estimated, with a t-statistic of -3.42, while the second is not, with a t-statistic of only -0.19. Overall, television appears to be highly seasonal, with a peak in January and a trough in the base month of May.

The day-of-week dummies acted as expected, with a large weekend increase. The weather variables also behaved as expected, with higher temperature and visibility causing less television watching, as people shift to outdoor activities, and with wind, clouds, and rain driving people indoors to the T.V. Snow had a negative effect, but was not precisely estimated.

In a further attempt to abstract from mere seasonal variation, 7-day first differences were calculated. The new regression is presented in Ta. 3-4. The variables prefixed with the letter D are the same as the previous regression, only having undergone first-differencing.

The results for visibility are still negative, but the effect is less precisely estimated, with only a 1.06 t-statistic.

TABLE 3-4

Percent of Households Using Television at 2:00 P.M. 1978-79:
7-Day First-Differences

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T RATIO	PROB>|T|
INTERCEPT	1	0.063820	0.174468	0.3658	0.7146
D7RA	1	0.024183	0.007834551	3.0867	0.0021
D7SN	1	-0.000163412	0.007373556	-0.0222	0.9823
D7WIN	1	0.008463473	0.003586003	2.3601	0.0185
D7TCL	1	0.024703	0.004452127	5.5486	0.0001
D7VIS	1	-0.00419665	0.003943219	-1.0643	0.2876
D7TEM	1	-0.090849	0.015345	-5.9206	0.0001
D7FTBLSA	1	-1.629750	2.752302	-0.5921	0.5539
D7FTBLSU	1	-0.562519	2.791929	-0.2015	0.8404
D7CUBHOM	1	2.615677	0.528036	4.9536	0.0001
D7CUBAWA	1	0.695619	0.520638	1.3361	0.1819
D7HOL	1	1.373662	0.633384	2.1688	0.0304
D7FTBLHL	1	13.847987	1.597012	8.6712	0.0001
D7BLIZZ	1	4.136090	1.068155	3.8722	0.0001

SSE	15576.95	F RATIO	25.94
DFE	709	PROB>F	0.0001
MSE	21.970307	R-SQUARE	0.3223

3.2.3 Baseball

Two analyses were performed on baseball data. The first is an analysis of attendance data and relevant team information published for the Chicago Cubs during the 1978 and 1979 seasons. The second was an analysis of television viewing of the Cubs during the same two seasons. For both the same explanatory variables will be used.

The variables are all briefly described in Ta.3-5 with the results of the regression of attendance data. The results in Ta.3-6 are for the percent of Chicago metropolitan area households watching WGN Television at 2:00 P.M. during each game. Many similar and highly correlated variables were included in the regression. These include mainly statistics on team performance during the season, and opposing team characteristics. These results were not examined in detail. Instead, we merely noted the effects of visibility on attendance.

An increase in visibility of one mile increases gate attendance by approximately 125 people, although the effect is not precisely estimated. Interestingly, the effect of the same increase in visibility is to increase television watching of the Cubs by about 3,000 households, even though the total effect on television watching of all types is to decrease viewing by about 4,000 households. Perhaps picture quality is enhanced with the improved visibility. Whatever the case, both attendance and television increase.

Noll provided an estimate of the effect of ticket prices on attendance for an SMSA of population of around 3.5 million. Since Chicago has an SMSA of approximately 7 million, the effect is doubled, yielding a reduction in attendance of 380,000 persons per year for a one dollar increase in ticket price. Our measured visibility effect of 125 persons per game, multiplied by 81 games yields a total of 10,125 additional persons per year in gate

TABLE 3-5

Chicago Cubs Total In-Person Attendance, 1978-79

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T RATIO	PROB> |T|	VARIABLE LABEL
INTERCEPT	1	19137.39	60316800888	0.0000	1.0000	
M	1	1892.86	2421.542	0.7817	0.4362	MONDAY
T	1	-2010.47	1881.489	-1.0685	0.2878	TUESDAY
W	1	1438.35	1948.707	0.7381	0.4622	WEDNESDAY
F	1	-398.466013	2093.582	-0.1903	0.8494	FRIDAY
S	1	10936.11	1880.054	5.8169	0.0001	SATURDAY
SU	1	13464.3	1916.078	7.0270	0.0001	SUNDAY
M4	1	-10060.6	3186.865	-3.1569	0.0021	APRIL
M6	1	5966.58	2168.68	2.7512	0.0070	JUNE
M7	1	7907.502	3011.217	2.6260	0.0100	JULY
M8	1	10158.55	3905.221	2.6013	0.0107	AUGUST
M9	1	2512.577	4325.281	0.5809	0.5626	SEPTEMBER
DATE	1	-0.810883	38.412070	-0.2294	0.8190	LINEAR TIME TREND
LASTHOME	1	141.073569	167.978923	0.8398	0.4030	DAYS SINCE LAST HOME GAME
DOUBLE	1	3161.818	1845.086	1.7136	0.0897	DOUBLE HEADER
RA09	1	-33.978231	22.961630	-1.4798	0.1420	RAIN AT 9 AM
RA12	1	-25.077909	30.191844	-0.8306	0.4081	RAIN AT 12 NOON
RA15	1	15.898115	26.908620	0.5908	0.5560	RAIN AT 3 PM
TEM12	1	214.071109	82.563972	2.5928	0.0109	TEMPERATURE AT NOON
WINDOUT	1	1730.691	1503.111	1.1514	0.2523	DUMMY, EQUALS 1 WHEN WIND BLOWS OUT
VIS12	1	12.487959	14.521299	0.8600	0.3918	VISIBILITY AT NOON IN TENTHS OF A MILE
SOXPCT	1	-13109.2	17161.29	-0.7639	0.4467	SOX WINNING PCT
SOXPLAY	1	58050.9	60316800889	0.0000	1.0000	ZERO-ONE DUMMY
CHIFEST	1	-2027.13	3221.181	-0.6293	0.5306	DUMMY FOR CHICAGOFEST
IN RACE	1	3999.039	2317.196	1.7250	0.0874	DUMMY, ONE WHEN TEAM IN PENNANT RACE
CUBPCT	1	-19223.8	16608.63	-1.1575	0.2498	CUBS WINNING PCT
HMGMBK	1	-935.843864	312.870576	-2.9912	0.0035	GAMES BEHIND LEADER (CUBS)
SAMEDIV	1	-16637.5	14290.28	-1.1643	0.2471	1 WHEN OPPONENT IN SAME DIVISION
CPTCHERA	1	680.158836	405.725853	1.4003	0.1645	CUB PITCHERS ERA
VSSTAN	1	-998.082156	405.395244	-2.0562	0.0423	VISITORS STANDING IN DIVISION
VPTCH500	1	179.609536	176.324238	1.0186	0.3108	VISITING PITCHERS GAMES ABOVE 5
EQUALITY	1	-11718.5	13620.63	-0.8604	0.3916	DIFFERENCE IN WINNING PCT
EQUALSD	1	24302.13	15857.92	1.5325	0.1285	EQUALITY X SAMEDIV
KINGMAN	1	-3335.01	1724.915	-1.9334	0.0560	DUMMY, ONE WHEN KINGMAN PLAYED
YEAR79	1	8823.667	13533.4	0.6520	0.5159	YEAR DUMMY
CUBWIN10	1	1059.82	560.594588	1.8639	0.0652	NO. OF GAMES WON OF LAST TEN

SSE	2G10887601	F RATIO	12.76
DFE	101	PROB>F	0.0001
MSE	25850372	R-SQUARE	0.8155

TABLE 3-6

Chicago Cubs Television Audience, 1978-79:

Percent of Households

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T RATIO	PROB> |T|	VARIABLE LABEL
INTERCEPT	1	28.310590	27804381	0.0000	1.0000	
M	1	1.508206	1.116264	1.3511	0.1797	MONDAY
T	1	-0.333530	0.867315	-0.3846	0.7014	TUESDAY
W	1	0.336566	0.898300	0.3747	0.7087	WEDNESDAY
F	1	0.895605	0.965083	0.9280	0.3556	FRIDAY
S	1	4.545163	0.866653	5.2445	0.0001	SATURDAY
SU	1	5.355864	0.883259	6.0638	0.0001	SUNDAY
M4	1	-1.992947	1.469057	-1.3566	0.1779	APRIL
M6	1	2.428024	0.999702	2.4287	0.0169	JUNE
M7	1	3.579786	1.388088	2.5789	0.0114	JULY
M8	1	6.405515	1.800199	3.5582	0.0006	AUGUST
M9	1	5.339600	1.993835	2.6781	0.0086	SEPTEMBER
DATE	1	-0.018761	0.017707	-1.0595	0.2919	LINEAR TIME TREND
LASTHOME	1	-0.066878	0.077434	-0.8637	0.3898	DAYS SINCE LAST HOME GAME
DOUBLE	1	0.364654	0.850534	0.4287	0.6690	DOUBLE HEADER
RA09	1	0.001897492	0.010585	0.1793	0.8581	RAIN AT 9 AM
RA12	1	0.032381	0.013918	2.3266	0.0220	RAIN AT 12 NOON
RA15	1	-0.010960	0.012404	-0.8836	0.3790	RAIN AT 3 PM
TEM12	1	0.042599	0.038060	1.1193	0.2657	TEMPERATURE AT NOON
WINDOUT	1	0.370211	0.692893	0.5343	0.5943	DUMMY, EQUALS 1 WHEN WIND BLOWS OUT
VIS12	1	0.010100	0.006693918	1.5089	0.1344	VISIBILITY AT NOON IN TENTHS OF A MILE
SOXPCT	1	12.036824	7.910881	1.5216	0.1312	SOX WINNING PCT
SOXPLAY	1	110.357756	27804381	0.0000	1.0000	ZERO-ONE DUMMY
CHIFEST	1	-2.988367	1.484876	-2.0125	0.0468	DUMMY FOR CHICAGOFEST
IN RACE	1	-0.115474	1.068163	-0.1081	0.9141	DUMMY, ONE WHEN TEAM IN PENNANT RACE
CUBPCT	1	-16.721749	7.656122	-2.1841	0.0313	CUBS WINNING PCT
HMGMBK	1	-0.520589	0.144225	-3.6096	0.0005	GAMES BEHIND LEADER (CUBS)
SAMEDIV	1	-7.081642	6.587425	-1.0750	0.2849	1 WHEN OPPONENT IN SAME DIVISION
CPTCHERA	1	-0.279615	0.223906	-1.2488	0.2146	CUB PITCHERS ERA
VSSTAN	1	-0.081824	0.223754	-0.3657	0.7154	VISITORS STANDING IN DIVISION
VPTCH500	1	-0.034274	0.081281	-0.4217	0.6742	VISITING PITCHERS GAMES ABOVE 5
EQUALITY	1	-10.780878	6.278732	-1.7170	0.0890	DIFFERENCE IN WINNING PCT
EQUALSD	1	9.484610	7.310063	1.2975	0.1974	EQUALITY X SAMEDIV
KINGMAN	1	0.592985	0.795138	0.7458	0.4575	DUMMY, ONE WHEN KINGMAN PLAYED
YEAR79	1	9.447361	6.238523	1.5144	0.1331	YEAR DUMMY
CUBWIN10	1	0.599823	0.262106	2.2885	0.0242	NO. OF GAMES WON OF LAST TEN

SSE	554.802019	F RATIO	7.18
DFE	101	PROB>F	0.0001
MSE	5.493089	R-SQUARE	0.7134

attendance per mile increase in visibility. Thus, the change in consumer's surplus associated with increase in visibility is at least 2.7 cents per person in attendance, or approximately $30,000 for a typical season's attendance. This benefit of a one mile visibility improvement represents somewhat less than one million dollars per year for baseball attendance in the entire U.S., assuming a homogeneous population.

three stand out. In the earliest study, Davis and Knetsch (DK) compared willingness to pay elicited in contingent valuation with a valuation derived through a travel cost model of demand. DK found the two estimates to be strikingly similar in magnitude. However, later work by Bishop and Heberlein (BH) suggested that the similarity found by DK might be misleading. Three of the BH results are relevant. First, travel cost valuations computed by BH were found to vary widely depending upon the choice of elements included in the cost of travel index that serves as price. Thus, a single travel cost estimate may be unreliable as a datum. Second, when compared to a range of travel cost estimates, the contingent valuation estimate lay close to the mean of the travel cost valuations. Third, both contingent and travel cost valuations tended to underestimate the BH datum of true value. In a third and most recent comparative study, Brookshire _et al_. found, in a manner consistent with a theory of individual versus market valuations, that valuations of visual air quality based on contingent valuation tended to lie below those based upon a rent gradient estimated on residential property prices. In light of the results of previous studies, two tentative conclusions can be drawn. First, contingent valuation performs at least as reliably as the operational, alternative valuation techniques. Results presented below tend to corroborate previous research.

3.3.1.1 Early Analysis of Hancock Tower Visitation

The Hancock Tower offered an unusual opportunity to determine the effects of visibility on the demand for view services. The view offered by the Tower is particularly sensitive to changes in visual range. Since an explicit price is charged and attendance is recorded it was possible to provide an estimate of the demand for Hancock Tower view services as a function of admission price, visibility, and a set of demand shifters. A mean per person consumer surplus of $2.12 in 1981 prices was computed from the aggregate demand estimate. Extrapolating this benefit estimate to cover the entire eastern United States is equivalent to assuming that identical viewing opportunities (as the Chicago urban landscape and skyline) exist in the entire eastern region. Assuming that similar experiences are obtainable in other areas of the region, then, given a homogeneous population, the aggregate consumer surplus is 275 million dollars in 1981 prices.

Early empirical analysis of Hancock Tower visitation completed four objectives. First, the error structures resulting from previously specified models were examined for non-random patterns and remedial estimation procedures employed where appropriate. Second, having selected appropriate estimation procedures, lagged groups of independent variables were tested for explanatory power. Third, the functional form of the specified equation was evaluated. Fourth, preliminary estimates of consumer surplus and revenue were computed for changes in visibility at the site.

The empirical analyses began with a demand equation specified in inverse exponential [IE] form. Such a functional form appeared most consistent with the color contrast results of Malm and Leiker. An examination of the error structure resulting from estimation in the IE form revealed a clearly non-random pattern. To remedy this difficulty, two steps were taken. First, the model was respecified in a simple linear form. The linear form was chosen since it can be viewed as a first-order approximation to more complex functional relationships. Second, a modified Cochrane - Orcutt (C-O)[1] procedure was used to allow for serial correlation errors and their effect on estimation. Combining the linear form with the C-O procedure resulted in an error structure approximating an i.i.d. process and, thus, appropriate for the computation of covariance statistics.

The second step in the empirical analysis was to check the explanatory power of lagged groups of variables. Conceptually, lagged variables could be important for two reasons. First, if the visiting population is fairly constant, extremely favorable visibility and weather conditions on a given day would tend to deplete the visitor stock for the nest. Within this context, lagged variables would tend to carry signs opposite to those of the respective comtemporaneous variable. Second, individuals may form expectations on the basis of past realizations of visibility and weather variable. In this context, the signs of lagged variables would depend upon the particular processes used to form expectations. Given this ambiguity, the net effect on the signs and significance of lagged variables cannot be determined *a priori*

To determine the empirical effect of lagged independent variables, F statistics (Chow type test) were computed to test several hypotheses. The basic form of the null hypothesis was : H_o - the lags x,y, and z do not contribute to variation in visitation. The set of variables lagged were VS1, VS2, RA, SN, CL, WIN, TEMP, and FG (see Ta. 3-7 for variable description).

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[1]See SAS AUTOREG procedure, SAS Institution, 1980.

TABLE 3-7

Statistic and Variable Descriptions
for Visitation, Weather and Visibility [1]

VARIABLE NAME	MEAN	STANDARD DEVIATION	DESCRIPTION
VST	955.12	710.77	Daily Ticket sales at Hancock Tower
VS1	12.55	13.94	Visibility in miles from H.T., 1st reading
VS2	16.28	15.42	Visibility in miles from H.T., 2nd reading
RP	0.7690	0.07659	Admission price divided by C.P.I.
RPI	916.91	9.23	Personal Income (National) divided by C.P.I.
M,TU,W, F,S,SU	0.14	0.35	Day of week dummy variables
TIME	270.50	151.41	Linear trend variable runs from 1 to 524
SNX	0.2169	0.6896	SINE Values with period of 365 days. Intended to pick up seasonal cycle
CSX	.01215	0.6922	COSINE Values with period of 365 days. Intended to pick up seasonal cycle
RA	0.0700	0.1950	Proportion of days with rainfall
SN	0.0719	0.2145	Proportion of days with snowfall
CL	0.4727	0.3262	Average cloud cover measured from 0 to 1.
WIN	10.82	3.983	Average windspeed in Knots
TEMP	50.72	22.09	Temperature in degrees Fahrenheit
FG	0.08715	0.2418	Proportion of days with fog

[1] Observations are for the period Iron 1/9/81 to 6/15/81.
Weather observations are for O'Hare Int. Airport.

The lags tested were lags 1,2,3,7,8 versus lags 1,2,7; lags 1,2,7 versus lags 1,7; lags 1,7 against lag 1; and lag 1 against an equation with no lags. The statistic used for testing was

$$F = (SSE_{H_0} - SSE_{H_1})(DFE_{H_1})/(SSE_{H_1})(DFE_{H_0} - DFE_{H_1}) \cdot$$

where SSE_{H_0} is the sum of squared errors resulting from the regression without lags x,y, and z; DFE_{H_0} is the degrees of freedom associated with SSE_{H_0}; and SSE_{H_1} and DFE_{H_1} are analogous quantities for the regression with lags x,y,z included.

Ta. 3-8a and 3-8b exhibit the results of regressions computed with various sets of lagged variables. At the 5 percent level, Chow test computed from the given statistics failed to reject any of the null hypotheses involving lagged groups of variables. Hence, none of the lagged groups of variables are shown to contribute to the variation in visitation. Additionally, inspection of Ta. 3-8a and 3-8b shows that the lagged variables contribute little to the long run effects on visitation. For example, the combined effect of VS1 and VS2 in the regression with no lags differs little from the long run effects when lags are included. Similar results are apparent for other variables such as RP and PR1. With their effects neither statistically nor absolutely significant, lagged effects are provisionally rejected in favor of the more parsimonious contemporaneous equation.

With a satisfactory specification of demand for Hancock Tower visitation, consumer surplus and revenue changes were estimated for various percentage changes in mean visibility. Results appear in Ta. 3-9. For these

TABLE 3-8a

LAGGED VARIABLES AND THEIR LONG RUN EFFECT ON VISITATION

	LONG RUN COEFFICIENTS[1]					
	LAGS					
EXPLANATORY VARIABLES	1,2,3,7,8	1,2,7	1,7	1	NONE	NONE (US1 DROPPED)
ΣVS1[2]	-4.38	-3.90	-4.15	-1.77	2.49	——
					(1.49)	
ΣVS2	11.13	13.29	12.60	12.05	7.10	8.49
					(4.63)	(7.17)
ΣRA	-445.83	-527.45	-462.84	-403.52	-535.89	-541.86
					(-5.87)	(-5.94)
ΣSN	-188.07	-127.25	-69.83	-125.31	-175.38	-183.07
					(-2.07)	(-2.16)
ΣCL	-143.02	-221.92	173.64	-226.86	-169.03	-174.83
					(-3.05)	(-3.17)
ΣWIN	6.19	-11.92	6.52	1.92	2.26	2.00
					(0.52)	(0.46)
ΣTEMP	1.81	2.08	0.81	3.26	5.70	5.16
					(2.75)	(2.50)
ΣFG	-283.03	-271.74	-457.33	-317.19	-316.38	-317.97
					(-3.90)	(-3.92)
RP	-1615.83	-1752.92	-1908.37	-1360.15	-1492.49	-1376.04
	(-2.00)	(-2.23)	(-2.50)	(-1.79)	(-2.05)	(-1.85)
RPI	23.04	23.34	26.77	25.33	24.21	23.76
	(1.98)	(2.05)	(2.38)	(2.29)	(2.21)	(2.17)
M	-6.44	0.41	7.68	-9.30	-13.59	-11.90
	(-0.09)	(0.00)	(0.11)	(-0.13)	(-0.19)	(-0.17)
TU	-66.55	-64.82	-66.71	-74.58	-64.75	-63.62
	(-0.93)	(-0.92)	(-0.96)	(-1.08)	(0.94)	(-0.93)
W	-29.26	-37.70	-43.20	-67.97	-60.14	-56.92
	(-0.47)	(-0.62)	(-0.72)	(-1.14)	(-1.01)	(-0.97)
F	311.55	302.03	311.95	292.21	295.83	299.01
	(4.95)	(4.91)	(5.15)	(4.92)	(4.98)	(5.06)
S	1071.55	1070.22	1074.62	1058.59	1063.66	1072.28
	(14.90)	(15.18)	(15.40)	(15.35)	(15.43)	(15.62)
SU	319.21	315.91	320.65	314.64	315.99	321.99
	(4.30)	(4.31)	(4.45)	(4.39)	(4.41)	(4.51)
TIME	1.73	1.77	1.99	1.69	1.71	1.61
	(2.57)	(2.70)	(3.09)	(2.68)	(2.80)	(2.60)
SNX	-10.22	16.38	14.16	-4.30	29.20	14.81
	(-0.12)	(0.21)	(0.19)	(-0.06)	(0.42)	(0.21)
CSX	-407.94	-389.01	-437.34	-359.99	-303.30	-311.59
	(-2.99)	(-3.24)	(-3.36)	(-3.99)	(-3.88)	(-4.00)
INT	-19638.55	-19777.28	-22861.00	-22078.96	-21086.09	-20688.35
	(-1.80)	(-1.35)	(-2.16)	(2.12)	(-2.04)	(-2.01)
ΣVS1+ΣVS2	6.75	9.39	8.45	10.28	9.59	8.49

t values given in parentheses

[1] Coefficients estimated using the SAS AUTOREG procedure with autocorrelation coefficients estimated at laggs 1 and 7.

[2] Σ indicates the sum of the coefficients of both contemporaneous and lagged values of the particular explanatory variable. For example, if lags 1 and 7 are included, ΣVS2 gives the sum of the coefficients estimated on the contemporaneous value of VS2 and the values of VS2 at lags 1 and 7.

TABLE 3-8b

Statistics for Regressions [1]

		LAGGED EXPLANATORY VARIABLES			
REGRESSION WITH LAGS	SSE	D.F.	R^2	p_1	p_7
1,2,3,7,8	62693407	464	.65	.31 (7.54)	.14 (3.39)
1,2,7	63477889	480	.64	.32 (7.66)	.15 (3.55)
1,7	64670558	488	.64	.32 (7.72)	.14 (3.35)
1	65825254	496	.62	.32 (7.72)	.13 (3.28)
NONE	67334226	504	.63	.32 (7.66)	.13 (3.26)
NONE (VS1 DROPPED)	67518458	505	.62	.32 (7.66)	.13 (3.16)

t values in parentheses

[1]Autoregressions estimated with autocorrelation coefficients estimated at lag 1(p_1) and lag 7 (p_7)

TABLE 3-9

Consumer Surplus and Revenue Estimates

Derived from Linear Demand Function [1]

CHANGE IN MEAN VISIBILITY ($\overline{VS2}$ = 16.28)	AVERAGE DAILY CHANGE[2]			
	CONSUMER SURPLUS	REVENUE	TOTAL	TOTAL
10%	26	28	54	19710
20%	52	57	109	39785
30%	78	85	163	59495
40%	105	113	218	79570
50%	133	115	248	90520

[1] Estimated from regression without interaction term as reported in Table 4. In dollars.

[2] Adjusted to current dollars using April 1981, C.P.I. of 266.8.

computations the regression "None (VSI Dropped)" of Ta. 3-8a was used along with the mean variable values given in Ta. 3-7. Revenue changes were included since, at this point, it is assumed that additional visitors are admitted to the Tower at close to zero marginal cost.

Caution must be taken against placing too much weight on the estimates Of Ta. 3-9. As Ta. 3-10 demonstrates, the response of individuals *to* changes in visibility is very likely non-linear. Ta. 3-10 gives results for two regressions. The first regression, "No Interaction," is entirely linear in the coefficients of all included variables. Note that the coefficient on visibility is rather small. The second regression, "With Interaction Term," includes two terms for visibility. The first is simply VS2. The second is

$$VST2 > 10 = VST \times D ,$$

where

$$D = 1 \text{ if } VST2 > 10 \text{ miles ,}$$
$$= 0 \text{ otherwise.}$$

The regression "With Interaction" clearly demonstrates a differential response to different ranges of visibility. When visibility is less than 10 miles the response in visitation to a one mile change in visibility is 23.91 versus the 8.49 person response of "No Interaction." When visibility is initially greater than 10 miles, the response to a one mile change in visibility is 9.6 (=23.91 - 14.31) and still greater than the 8.49 person response of "No Interaction." From these results, two implications can be drawn. First, non-linear forms should he explored for fit to the Hancock data; second, consumer surplus and revenue simulations performed with the "With Interaction" regression or other non-linear forms are likely to result in significantly larger estimates.

TABLE 3-10

TESTING FOR NON-LINEAR RESPONSE TO VISIBILITY

	REGRESSION RESULTS	
EXPLANATORY VARIABLE	NO INTERACTION TERM FOR US2	WITH INTERACTION TERM
INT	-20688.85 (-2.010)	-20640.20 (-2.00)
VS2	8.49 (7.17)	23.91 (3.47)
VS2 > 10	———	-14.31 (-2.27)
RP	-1376.04 (-1.85)	-.1416.66 (-1.90)
RPI	23.76 (2.17)	23.68 (2.17)
M	-11.90 (71.80)	-12.68 (-0.18)
TU	-63.62 (-0.93)	-59.36 (-0.86)
W	-56.92 (-0.97)	-45.23 9-0.76)
F	299.01 (5.06)	313.52 (5.26)
S	1072.28 (15.62)	1095.40 (15.74)
SU	321.99 (4.51)	344.40 (4.77)
TIME	1.61 (2.60)	1.61 (2.60)
SNK	14.81 (0.21)	21.20 (0.30)
CSX	-311.59 (-4.01)	-310.95 (-4.00)
RA	-541.86 (-5.94)	-540.29 (-5.95)
SN	-183.01 (-2.16)	-171.16 (-2.03)
CC	-174.83 (-3.17)	-183.05 (-3.33)
WIN	2.00 (0.46)	1.64 (0.38)
TEMP	5.16 (2.50)	5.24 (2.55)
FG	-317.97 (-3.92)	-307.89 (-3.81)
R^2	0.62	.62
SSE	67518458	66831464
DF	505.	504.

t values in parentheses

3.3.2 The General-Choice Model

The activity or action of record at HTO is not the enjoyment of viewing services but the number of individuals purchasing access to the viewing site. At any particular admission price, the quantity of access supplied is assumed to be perfectly elastic within the range of realized visitation. Given this perfect elasticity of supply, a demand function can be estimated through simple regression techniques and without reference to problems of simultaneity.

The demand for access to HTO may be thought of as derived from an individual's use of access in producing viewing services given the characteristics of the observatory, the city skyline, and environmental conditions including visibility. The most notable aspect of demand is that, at the individual level, it is discrete: an individual either accesses Tower services or does not. Borrowing from the relevant literate on discrete choice (Domencich and McFadden), aggregate demand can be represented by

$$VST_t = N_t \pi \quad , \tag{3-1}$$

where VST_t is total visits on day t, N_t is a pool of potential visitors on day t, and π is the probability that an individual in N_t visits the HTO. More specifically, π is the probability that the utility gained by an individual through a set of activities that includes an HTO visit is greater than the utility of all sets of activities that do not include a visit to HTO.

Variables relevant to the determination of N_t and τ can be identified by considering the abbreviated "decision tree" (Domencich and McFadden) given in Fig. 3-1. On any particular day one can imagine that individuals sort themselves out over mutually exclusive activities as indicated by the direction of the arrows in Fig. 3-1. However, as the literature on discrete choice points out, the flow of information and choice is just the reverse of the sequence of actions. That is, individual choice begins at Branch 4 in Fig. 3-1. To make the Branch 3 decision between downtown activities and other alternatives, the individual must first select the optimal package of downtown activities. The decision at Branch 3 can then be made optimally by comparing the utility gained from the best set of downtown activities with the utility gained from the best set of alternative activities.

To identify variables relevant to choice, decisions represented in Fig. 3-1 are partitioned into those made in the longer run and those made in the short run. For example, choices above Branch 3 are likely to require major commitments of personal resources and be relatively fixed by long term contracts. For these long run decisions, the most important variables to the HTO visit choice are likely to be time series variables. Clearly, for the individual, relative prices contemporaneous to the long run decision may be inportant indicators of future relative prices. However, in the research problem at hand, this portion of the the individual's information set remains unobservable and must be relegated to an error term. Time series variables, however, are observable and are likely to be quite pertinent to long run individual planning. For instance, seasonal merchandizing sales and weather conditions are probably best judged by seasonal or other time series variables

FIGURE 3-1

Decision Tree for Choice of Activities

Branch 1	Location	
Branch 2	Metropolitan Chicago (N_M)	Other (N_O)
Branch 3	Leisure (N_{ML})	Work (N_{MW})
Branch 4	Downtown Activities (N_{MLD})	Other (N_{MLD})
	Activity Sets Including HTO	Activity Sets Excluding HTO

Specifically, for purposes of long run decisions, an individual can expect prices at downtown shopping areas to be relatively high in December but low in January; it is likely to be cooler in January than in July but whether January 1 or January 7 is colder is largely a matter of random occurrence. In addition, day of week effects may enter due to conventions of a 40 hour workweek and work scheduling. For the long run decisions of location and work/leisure choice, the information (potentially observable by the researcher) passed back up the decision tree therefore depends largely upon seasonal and other time series considerations. Thus, if decisions above Branch 3 are primarily long run decisions, we can write the pool of potential HTO visitors on day t at Branch 3 as a function

$$N_{tML} = N_{tML}(s,d,e) \quad , \tag{3-2}$$

where s is a vector of time series variables, d is a vector of day of week dummy variables, and e is an error term introduced for unknown price information used by individuals.

For individuals within N_{tML}, a decision regarding the day's excursion must be made. Assuming that the choice between downtown and other activities is fairly decisive and that variables specific to HTO contribute rather little to choice at Branch 3[1], the only variables affecting choice at Branch 3 that are also potentially observable by the researcher are local weather conditions. Entering these local weather conditions as a determinant of the visitor pool,

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[1] The assumption is not entirely unreasonable. Of the individuals sampled at HTO, 75 percent indicated that their visit HTO was only a sidetrip and apparently not crucial to their visit downtown.

we can write

$$N_{tMLD} = N_{tMLD}(s,d,w,e) \quad (3\text{-}3)$$

where w is a vector of weather and environmental variables and e is again an error term introduced for unobservables.

It is at Branch 4 that we can begin to model individual choice and determine the relation between visitation, $N_{tMLDH}=VST_t$, and admission ticket prices. To begin, we assume that an individual maximizes a homothetic utility function subject to an excursion budget constraint prices, and environmental conditions. Maximization is conditional upon the HTO visit/non-visit choice[2] and we suppose that for all individuals the HTO visit is a sidetrip, an addition to an otherwise fixed itinerary. For a typical individual or group of individuals, conditional indirect utility funcitons are

$$v_h(m-np_h) = v_h(p,w)(m-np_h) \quad (3\text{-}4)$$

if the individual visits the HTO and

$$v_o m = v_o(p,w)m \quad (3\text{-}5)$$

if the individual does not visit the HTO where m is the excursion budget, p is a vector of prices of ordinary (continuous) market goods, w is again a vector of weather and environmental variables, n is the number of individuals within a typical visiting group, p_h is the price of admission, and np_h is the fixed cost of gaining access to HTO. Taking log transformations of (3-3) and (3-4), and letting $u_h = \ln v_h + \ln(m-np_h)$ and $u_o = \ln v_o + \ln m$, the probability that an individual i in N_{tMLD} visits HTO can be written

$$\pi_h = \text{Prob}(u_h + \varepsilon_{hi} > u_o + \varepsilon_{oi}) \quad , \quad (3\text{-}6)$$

---

[2] Small and Rosen have suggested the conditional maximization process in dealing with discrete choice.

where z_{hi} and z_{oi} are the respective deviations of individual utility from the utility of the typical individual. Eq. (3-1) can now be written

$$VST_t = N_{tMLD}\pi_h \tag{3-7}$$

$$= N_{tMLD}(s,d,w,e)\pi_h(p,w,m,n,p_h).$$

Assuming that z_h and z_o are extreme value or Weibull distributed, π_h can be written in terms of the cumulative logistic distribution (Domencich and McFadden):

$$VST_t = N_{tMLD}(\ v_h(m-np_h)/(\ v_h(m-np_h) + v_o m\ ))\ , \tag{3-8}$$

where $\pi_h=(v_h(m-np_h)/(v_h(m-np_h)+v_o m)$.

To proceed further with specification, specific funtional forms must be applied to N_{tMLD}, v_h, and v_o. For present purposes the most tractable functional form is the general Cobb-Douglas (CD) form, $x^a\exp(b+cy+e)$ where x is a continuous variable, y is a dummy variable, e is a log-normally distributed error term, and a, b , and c are the coefficients of interest. Applying this general CD form to the aggregate demand equation in eq. (3-8) an estimable form is

$$\ln VST_t = \ln A(s,d,w,p,e) + \ln(m-np_h) + \ln(v_h(m-np_h)+v_o m)\ , \tag{3-9}$$

where A(.) is of the form $x^a\exp(b+cy+e)$. Because we have no information on the typical excursion budget or group size of individuals in X_{tMLD}, the log terms which include m are replaced by first order Taylor series approximations. The approximation to be estimated is

$$\ln VST_t = a_1 + \ln A(s,d,w,) + b_1 p_h + \ln e\ , \tag{3-10}$$

where again A(.) is of the general CD form, a_1 is a constant term, and p_h enters the equation in level form with coefficient b_1.

Given an estimate of eq. (3-10), it can be shown by direct intergretion that approximate total surplus is defined by estimated visits, $\widehat{VST}$, divided by the coefficient of admission price, $\hat{b}_1$. Thus, approximate average or expected surplus obtained per person visiting HTO is

(3-11) $$AVCS = (\widehat{VST}/\hat{b}_1)\widehat{VST}$$
$$= 1/\hat{b}_1 \quad .$$

Because the error bounds on $\hat{b}_1$ are straightforwardly calculated, AVCS is selected as the basis of contrasting demand-based valuation with contingent valuation in the HTO case.

3.3.3 The Contingent Valuation Experiment

During the Spring of 1981, a contingent valuation instrument was designed that would elicit the maximum willingness to pay (MWTP) for access to HTO[3]. During the summer of 1981, contingent valuations of visiting groups at HTO were recorded. Valuations were obtained under a variety of environmental conditions and, by the end of the summer, 319 usuable observations had been recorded.

Ta. 3-11 displays the results of the contengent valuation experiment at HTO. MWTP is the maximum willingness to pay elicited. ADMCOST gives the average actual cost of admission. Average SURPLUS per group is MWTP minus ADMCOST or an average of 3.93 dollars. Finally, average GROUPSIZE was 2.67 for groups during the summer of 1981.

TABLE 3-11

Results of the 1981 Contingent Valuation Experiment
at the Hancock Tower Observatory

Variable	Sample Mean[1]	Standard Error
MWTP	9.43	.428
ADMCOST	5.50	.199
SURPLUS	3.93	.314
GROUPSIZE	2.67	.115

[1] Number of respondent groups was 319. Means in this Table are computed for groups, not individual persons. Covariance between SURPLUS and GROUPSIZE is 4.59.

During the Spring of 1981, the HTO management apparently decided to experiment with well-publisized price variations in order to determine the relationship between price and attendance. For the purpose of estimating demand, the price variation was sufficient enough for a statistically significant estimate of the coefficient on admission price as shown in Ta. 3-13. By using the variable definitions given in Ta. 3-14, it is clear that the overall specification of the estimated equation (Ta. 3-14) paralleled the identification given in eq. 3-10. Relevant statistics for the secondary data are given in Ta. 3-15.

The coefficient of central interest is the coefficient on admission price, the variable PP. By inverting the coefficient and using the approximation formulas given in Mood, Graybill, and Boes (p. 181) for quotients of random variables, average surplus, AVCS, was computed and is presented in Ta. 3-16. In the same Table and computed using the same approximation formulas, the average from contingent valuation (AVCV) is also given. Given the fairly large sample sizes, a z statistic was computed for the difference between AVCS and AVCV and is also given in Ta. 3-16. Quite clearly, the z statistic indicates no statistically significant difference between the two means at conventional levels of significance.

The Hancock Tower Observatory in Chicago offered conditions suitable estimates of both a demand based valuation of access to the Observatory and a contingent valuation of access. Given the functional form developed for aggregate demand, average consumer surplus per person-visit to the Tower

TABLE 3-13

Regression Estimates of an Aggregate Demand for Access to HTO, March 15 to May 31, 1981

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T RATIO	PROB>|T|
INTERCEPT	1	-33.479816	14.598137	-2.2934	0.0253
LNVIS	1	0.139551	0.054726	2.5500	0.0133
PP	1	-0.532835	0.192970	-2.7612	0.0076
MAR	1	0.327406	0.195630	1.6736	0.0994
MAY	1	-0.334280	0.125514	-2.6633	0.0099
M	1	-0.171819	0.181041	-0.9491	0.3464
TU	1	-0.348115	0.159548	-2.1819	0.0330
W	1	-0.126686	0.158907	-0.7972	0.4285
F	1	0.375736	0.158148	2.3758	0.0207
S	1	0.786929	0.158722	4.9579	0.0001
SU	1	0.271636	0.161977	1.6770	0.0987
RAIN	1	-0.926709	0.215838	-4.2935	0.0001
TSC	1	-0.00239967	0.001542321	-1.5559	0.1250
FOG	1	-2.295919	0.297832	-7.7088	0.0001
LNWIN	1	0.034347	0.128057	0.2682	0.7895
LNTMK	1	7.136954	2.612609	2.7317	0.0083
LNT	1	0.232934	0.116005	2.0080	0.0492
HAZE	1	-0.090610	0.395829	-0.2289	0.8197

	SSE	7.601226	F RATIO	24.90
	DFE	60	PROB>F	0.0001
DEP VAR: LNTVST	MSE	0.126687	R-SQUARE	0.8759

TABLE 3-14

Definitions of Variables Used in Estimating

Aggregate Demand

Variable[1]	Definition
LNVIS	Log of visibility where visibility is measured in miles.
PP	Price of admission to HTO in dollars.
MAR	Month of March dummy variable (March=1, 0 otherwise).
MAY	Month of May dummy variable (May=1, 0 otherwise).
M, TU, W, F, S, SU	Day of week dummy variables (No dummy variable entered for Thursday).
RAIN	Proportion of day in which rain fell.
TSC	Total sky cover in percent.
FOG	Proportion of day with fog.
LNWIN	Log of wind speed where wind speed is measured in mph/10.
LNTMK	Log of temperature where temperature is in degrees Kelvin.
LNT	Log of a time series variable beginning with 1 on March 15 and running consecutively through the intergers to 78 on March 31.
HAZE	Proportion of day with haze.

[1] All weather observations except visibility were recorded at O'Hare International Airport in Chicago. Visibility was recorded at HTO.

TABLE 3-15

Sample Statistics for Variables Used in

Estimating Aggregate Demand, March 15 to May 31, 1981

VARIABLE	MEAN +	STANDARD DEVIATION
LNTVST	6.58799580	0.89175811
LNVIS	2.56384683	1.12190785
PP	2.13141026	0.28411505
MAR	0.21794872	0.41552458
MAY	0.39743590	0.49253502
M	0.14102564	0.35030076
TU	0.14102564	0.35030076
W	0.14102564	0.35030076
F	0.14102564	0.35030076
S	0.14102564	0.35030076
SU	0.15384615	0.36313652
RAIN	0.11111111	0.25576565
TSC	69.35897436	32.98544737
FOG	0.06410256	0.20142130
LNWIN	2.40314246	0.37150081
LNTMK	5.65218864	0.02217227
LNT	3.39643141	0.91573362
HAZE	0.04273504	0.12436244
TVST*	931.61538462	567.76436101
VISB1**	20.26533862	15.42756495

* Total daily visits recorded at HTO.

** Visibility in miles recorded at HTO

+ Number of observations equals 78.

TABLE 3-16

Estimates of Mean Per Person Consumer Surplus

Obtained by Access to the HTO

Mean per person surplus from aggregate demand estimate (AVCS):	$2.12
Variance:	.462
Mean per person surplus from contingent valuation estimates (AVCV):	$1.47
Variance:	.0120
Test statistic:	z = (2.12 - 1.47) / .688
Conclustion:	Do not reject null hypothesis of no significant difference between AVCS and AVCV.

embodied the most desirable statistical properties. On the basis of a comparison of average estimated surpluses, the hypothesis of a statistically significant difference between demand-based and contingent valuation was rejected. Thus, consistent with the results of other researchers, contingent valuation is shown to perform at least as well as the next best operational alternative in valuation.

3.4 VIEW-ORIENTED RESIDENCES

Clean air and attractive vistas are firmly established as valuable dimensions of environmetnal quality. Analysis shows that there are substantial benefits derived from clean air and that it is a valuable resource indeed. Typical is the housing market analysis of Bender _et al._ (1980) which shows that for a uniform 20 percent reduction in particulate concentration in Chicago the average household is willing to pay approximately $600 per year. Using a survey approach Brookshire _et al._ (1982) estimate that the typical household is willing to pay approximately $310 per year for a 30 percent reduction in pollutant concentrations in Los Angeles. Further analysis shows that attractive views yield benefits to which approximately 9 percent of some house prices in Sydney (Abelson, 1979) and 15 percent of some rents in Chicago (Pollard, 1977) can be attributed. Rowe _et al._ (1980) find that people will bid approximately $100 per year for clear, unpolluted vistas in the Grand Canyon National Park Area.

This study takes as its point of departure an earlier paper, "Visibility, Views and the Housing Market" which suggests that intensive analysis of view-oriented submarkets of the residential housing market would be productive. The objectives of this research are: (1) to measure the values of views and view characteristics including visibility using a survey instrument which establishes a contingent market for each; (2) to measure the values of views and view characteristics using a hedonic-demand analysis of housing consumption for the same group surveyed and (3) compare the contingent values from the survey and the implicit values from the housing market for individuals dwelling in view-oriented residences.

To insure comparability, a survey was conducted among Chicago residents of high-rise buildings along Lake Michigan. The survey instrument was designed to elicit contingent values for views, view characteristics and visibility and to get from the same individuals sufficient information to estimate the values of some of the same amenities from their housing consumption. An abbreviated bidding game was used to obtain contingent values. During the period May through September 1981, a team of interviewers collected 208 responses from residents of 10 high-rise buildings located mostly north of Chicago's Loop. Although further verification was warranted, the integrity of the data was well enough established that some results can be reported.

3.4.1 Contingent Values for View-Oriented Residences

3.4.1.1 Willingness to Accept Payment for No View

Residents of units with relatively unobstructed views of the lake and/or Loop were asked how much their monthly housing payments would have to be reduced for them to choose a unit with no views. Of those who responded, 92 percent replied that the amount would have to be greater than $50; only 8 percent replied that they would choose a viewless unit for a $50 reduction. The mean of the responses to the query about the minimum amount individuals would be willing to accept for loss of view is $169.39. It should be noted that this is average for only 40 percent of the sample and does not incorporate the 60 percent who bid zero, an infinite amount or did not respond.

3.4.1.2 Willingness to Pay for Lake View

Residents who do not have an unobstructed view of the lake were asked how much their monthly housing payment could be increased if they got a good lake view. Of those who responded, 52 percent replied that the amount could be more than $30; 48 percent replied that they would choose their current unit without a lake view if the amount was $30 or more. The mean of the responses to the query about the maximum amount individuals would be willing to pay for a lake view is $43.06.

3.4.1.3 Willingness to Pay for a Unit which Is Ten Floors Higher

All residents were asked how much their monthly housing payments could be increased if they got otherwise identical units 10 floors higher than their current units. Of those who responded 73 percent replied that the amount would have to be less than $30; 27 percent replied that they would choose the higher unit even if the payments increased by $30. The mean of the responses to the query about the maximum amount individuals would be willing to pay for the higher unit is $25.32. The average is based on responses from 79 percent of the 208 people surveyed.

3.4.1.4 Willingness to Pay for Better Visibility

All residents were asked how much their monthly housing payments could be increased if they got more days with better atmospheric visibility. This improvement in visibility was described by showing residents 9 color photographs which depict three Chicago lakefront vistas under visibility conditions of 3 miles, 13 miles and 30 miles. These ranges occur throughout the year and under current conditions there may be 12 consecutive days of 3 mile visibility. The specified improvement would reduce to four the number of consecutive days with only three mile visibility. All people surveyed responded and 65 percent replied that the amount their monthly payments could increase would be $10 or more; 35 percent rplied thay they would choose current visibility conditions if they were to pay $10 per month. The mean of the responses to the query concerning the maximum amount individuals would be willing to pay for the improvement in visibility is $14.27. The average is based on responses from 99 percent of the 208 people surveyed.

3.4.1.5 Implicit Value from the Housing Market

Using the same survey instrument containing the contingent valuation experiments, data on housing consumption and consumer characteristics were collected. Some tentative estimated can be made from a housing hedonic equation for renters. The housing hedonic equation is

$$\text{(3-12)}\quad \text{RENT} = \underset{(2.90)}{100.96} + \underset{(3.77)}{28.950}\ \text{TOTROOMS} + \underset{(1.98)}{83.918}\ \text{BATES} + \underset{(1.75)}{0.0816}\ \text{AREA}$$

$$+ \underset{(3.31)}{41.995}\ \text{CARPET} + \underset{(0.72)}{19.994}\ \text{DISHWASH} + \underset{(2.67)}{2.6219}\ \text{FLOOR}$$

$$+ \underset{(0.09)}{0.0139}\ \text{WARUN} + \underset{(1.53)}{0.21135}\ \text{LWARA}$$

$R^2 = .8537$ $F = 28.44$ $n = 48$

where RENT is monthly rent in dollars, TOTROOMS is total rooms, BATHS is number of bathrooms, DISHWASH is 1 if the apartment comes furnished with a dishwasher and 0 if not, FLOOR is the number of floors up the apartment is in the building, WARUN us square feet of total window area with unobstructed view, and LWARA is square feet of window area with an unobstructed view of Lake Michigan. Of the view-related characteristics, FLOOR is significant at the 2 percent level, LWARA is significant at the 14 percent level, but WARUN is not significant at any reasonable level.

Estimates based on this housing hedonic equation may be biased and imprecise since (1) relevant housing characteristics may have been omitted, (2) the functional form of the hedonic housing equation may be nonlinear, (3) the benefits might have to be estimated from demand equations and not directly from the average hedonic prices, (4) the remaining 160 residents may differ from the 48 in the sample, and (5) data errors may remain.

3.4.1.6 Implicit Value of a Unit which Is Ten Floors Higher

The value of height and the associated breadth of view is obtained by multiplying the coefficient of FLOOR by the 10 floor change in height. The value of the increase in height is (2.6219)(10) = $26.22 per month. This value is remarkably close to the contingent value of $25.32 from the bidding experiment.

3.4.1.7 Implicit Value of a View

The value of a lake or Loop view would be obtained by adding the products of the coefficients of WARUN and LWARA with their respective changes in window area. Performing the calculation gives an implicit value which is appromi-mately one-third of the average contingent value. However, the difference could be easily due to 44 percent of the contingents bids being excluded from the sample and the (perhaps overly) restrictive definition of WARUN.

3.4.2 Estimates of the Values of Views and View Characteristics

The similarity of the contingent and implicit values for height (10 floors up), the high response rate on the bidding experiment and the highly significant coefficients in the renters' housing hedonic equation are favorable to the use of contingent value of better visibility for policy analysis. Aggregation of individual values over the population residency in the view-oriented submarket would be straightforward, but it must be recognized that this subgroup has high annual incomes (the average is $33,000) and is well-educated (the average is some graduate work). Values of views and visibility from this submarket must be considered in the social value of improved air quality, but they are likely to be higher than those values of the entire population which is less oriented to views, view characteristics and visibility.

3.5 AIR AND AUTO TRAFFIC

3.5.1 Visibility and Air Traffic

Lowered visibility imposes costs on air travelers in many ways. If visibility falls below three miles, all traffic must operate under Instrument Flight Rules (IFR). All general aviation for flight training or recreation which is not IFR rated must terminate. The people engaged in general aviation lose the benefits gained from flying, aircraft rental operators lose revenue, and airports also lose revenue from landing fees. Those still engaging in aviation experience losses in waiting time since aircraft must maintain greater increments between each other under IFR conditions. Not only do travelers experience time costs in queuing, but also may miss connecting flights or appointments. Under lowered visibility, the probability or air accidents also increases. If visibility is poor enough to cause an in-flight diversion, the traveler’s involved and airlines suffer losses. The nature of these costs are discussed in detail, and a formal economic model developed later in this section. This model captures consumer behavior under visibility constraints on air travel and provides a framework for measuring the net cost or benefits of lowered visibility on air travel.

In the next section, a generally used method of measuring the cost/benefit structure is outlined and critiqued. A formal model of utility maximization is presented. Finally, empirical estimates of visibility effects on total take-offs and landings at three Chicago area airports are presented and discussed within the context of the economic model.

One procedure used in estimating net benefits is to regress the affected variable on a vector of independent variables. In this case, air traffic counts would be regressed on visibility (possibly current and lagged), and a vector of other weather variables. The equation would resemble

$$(3\text{-}13) \qquad C_{it} = \alpha_o + \alpha_1 V_{it} + \underline{\alpha}_z \underline{W}_{it} + \varepsilon_{it} \quad ,$$

where C_{it} is traffic counts at the ith airport in period t. $\underline{W}_{it}$ and V_{it} are vectors of airport-specific weather and visibility variables in time t, and ε_{it} the stochastic error term. α_1 is taken to be the effect of changes in visibility on traffic counts. In log form α_1 is the elasticity of traffic counts with respect to visibility. Then an average value for a traffic count is determined and if α_1 = 10%, then a one percent change in α_1 would imply a 10 percent decrease in counts. So the number of counts lost times the average value is the cost of decreased visibility.

When presented in this way, several important points emerge. Besides the obvious problem is assessing the value of a count lost, α_1 is neither a supply nor a demand elasticity. It is an amalgam of supply and demand effects. Consider the simple supply and demand structure:

$$(3\text{-}14) \qquad C^D = \gamma_1 V_t + \underline{\gamma}_2 \underline{W}_t + \gamma_3 P_c$$

$$(3\text{-}15) \qquad C^S = \beta_1 V_t + \underline{\beta}_2 \underline{W}_t + \beta_3 P_c \quad .$$

Setting counts supplied (C^S) equal to counts demanded (C^D) yields a reduced form equation for the equilibrium counts (C_E):

$$(3\text{-}16) \qquad C_E = \left(\frac{1}{\gamma_3} - \frac{1}{\beta_3}\right)^{-1} \left[\left(\frac{\gamma_1}{\gamma_3} - \frac{\beta_1}{\beta_3}\right) V_t + \left(\frac{\gamma_2}{\gamma_3} - \frac{\beta_2}{\beta_3}\right) \underline{W}_t \right] \quad .$$

If eq.(3-13) and (3-14) were the true underlying structure of supply and demand, then $\alpha_1 = (\frac{1}{\gamma_3} - \frac{1}{\beta_3})^{-1} (\frac{\gamma_1}{\gamma_3} - \frac{\beta_1}{\beta_3})$; where γ_3 is the price elasticity of counts demanded, β_3 is the price elasticity of supply, γ_1 is the visibility elasticity of demand and β_1 is the visibility elasticity of supply, Clearly, interpreting α_1 as an elasticity is incorrect. In fact, α_1 cannot be shown to be an upper or lower limit of the true underlying elasticities since the sign of $(\frac{\gamma_1}{\gamma_3} - \frac{\beta_1}{\beta_3})$ is ambiguous.

Even if α_1 could be shown to be a limiting case of the underlying parameters, just multiplying α_1 times the count value does not give a true social cost. The count value chosen is usually an aircraft rental fee, or a plane ticket price. These are at best lower bound estimates of the true cost of the delays. They do not include the social cost due to inefficient allocation of resources.

In this section, the problems of infering social cost estimates from reduced form equations with no underlying structural model have been discussed. The importance of structural models in interpreting reduced form coefficients was shown.

3.5.2 A Model of Air Traffic Responses to Lowered Visibility

Air transportation is an input to a demand for location change. Y, or location changes, is the produced good directly entering the utility function. In meeting the demand for a Y, the individual choses the lowest cost combination of productive inputs. Among the possible combinations is air travel, either purchasing a ticket on a commercial airline or chartering a flight.

There is also a time input involved which is the trip to the airport, the time of the trip itself, and waiting time. Visibility affects the time componenet of air transportation by increasing the landing or takeoff queue. Consequently, the magnitude and direction of the visibility effects on purchased inputs can be analyzed. The purchased input on which the analysis focuses, in the aggregate, is the number of take-offs and landings per day in Chicago area airports. The model presented below develops a method of estimating the true social cost of visibility changes on Y by analyzing effects in the input, or counts, market.

Following Tolley (1972), the demand curve for Y is

(3-17) $\quad P_y = F(Y)$,

where Y is produced according to

(3-18) $\quad Y = Y(z,v)$,

v is the level of visibility which acts as a cost shifter. That is, changes in v affect the amounts of x needed to produce the same level of Y. From this framework the marginal cost of Y can be derived:

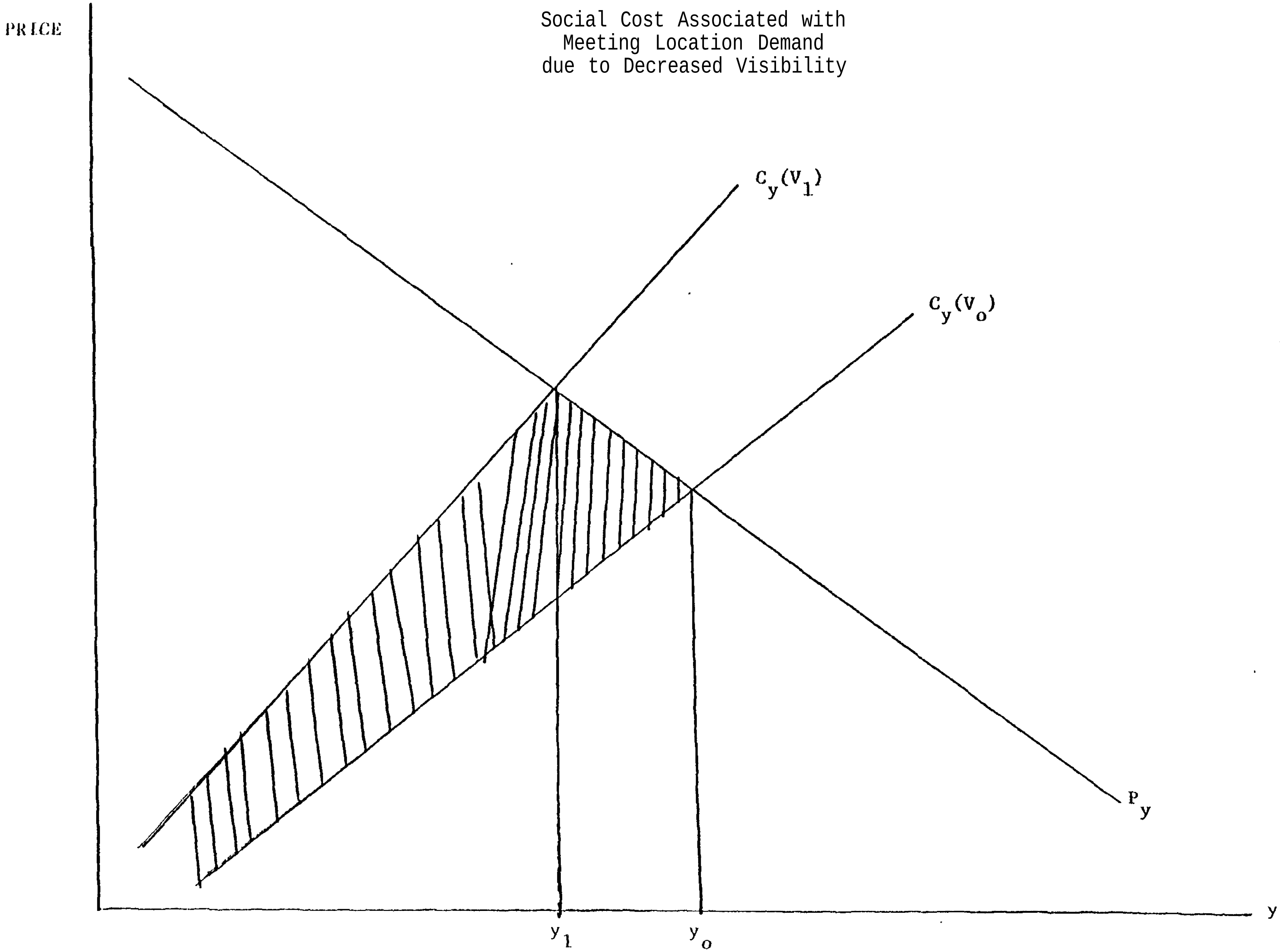
(3-19) $\quad P_y = P_z \left(\frac{1}{y_z(z,v)}\right)$

The right hand side of (3) is the marginal cost of producing Y, and y_z is the marginal productivity of z in the production of Y.

The question to address is what are the costs associated with a decrease in visibility in the framework presented by eq. (3-17) and (3-19). Fig. 3-2 reproduced from the Tolley paper, shows that a decrease in visibility shifts the cost curve back, while leaving demand for Y unaffected. The social cost associated with this shift is the shaded area. The analytic solution of the area is

FIGURE 3-2

Social Cost Associated with
Meeting Location Demand
due to Decreased Visibility



$$(3\text{-}20) \quad C_y(v) = \int_{Y_o}^{Y} P_y \, Y_{zv} dY \ ,$$

where Y_{zv} is the effect on the marginal productivity of z of a change in v. In order to view this cost in the framework of a model for counts, this area must be transformed.

By substituting eq.(3-19) into eq.(3-20), this area is

$$(3\text{-}21) \quad C_z(v) = \int_{z_o}^{z_1} P_z \frac{Y_{zv}}{Y_z} dz \ .$$

P_z is the supply curve for z, and $\frac{Y_{zv}}{Y_z}$ can be viewed as the percentage change in z's marginal productivity resulting from the change in visibility.

The graphical analog to (3-21) is shown in Fig.3-3. P_z is an upward sloping supply curve for 2. $D_z(v_0)$ is the demand for z derived from the demand for Y under visibility v_0. $D_z(v_1)$ is the demand for z at the lower visibility level v_1. The cast associated with this fall in demand is the shaded area in Fig.3-3. So, if P_z were invariant to changes in visibility, the area ABC would be the associated social cost.

Now, consider the problem of a shift in P_t due to a change in visibility. The supply curve P_t can be viewed as the standard supply curve of an exhaustible resource. Fig. 3-4 presents the supply of counts curve for an airport. As p^*, the landing fee associated with this particular airport, the supply of counts is completely elastic up to $\bar{z}$, the technological or legal bound on the number of counts which can be supplied per period. The effect of decreased visibility is to add queuing time due to in-air stack ups

FIGURE 3-3

Social Cost of Supply Shift Transformed
to the Input Market for Counts

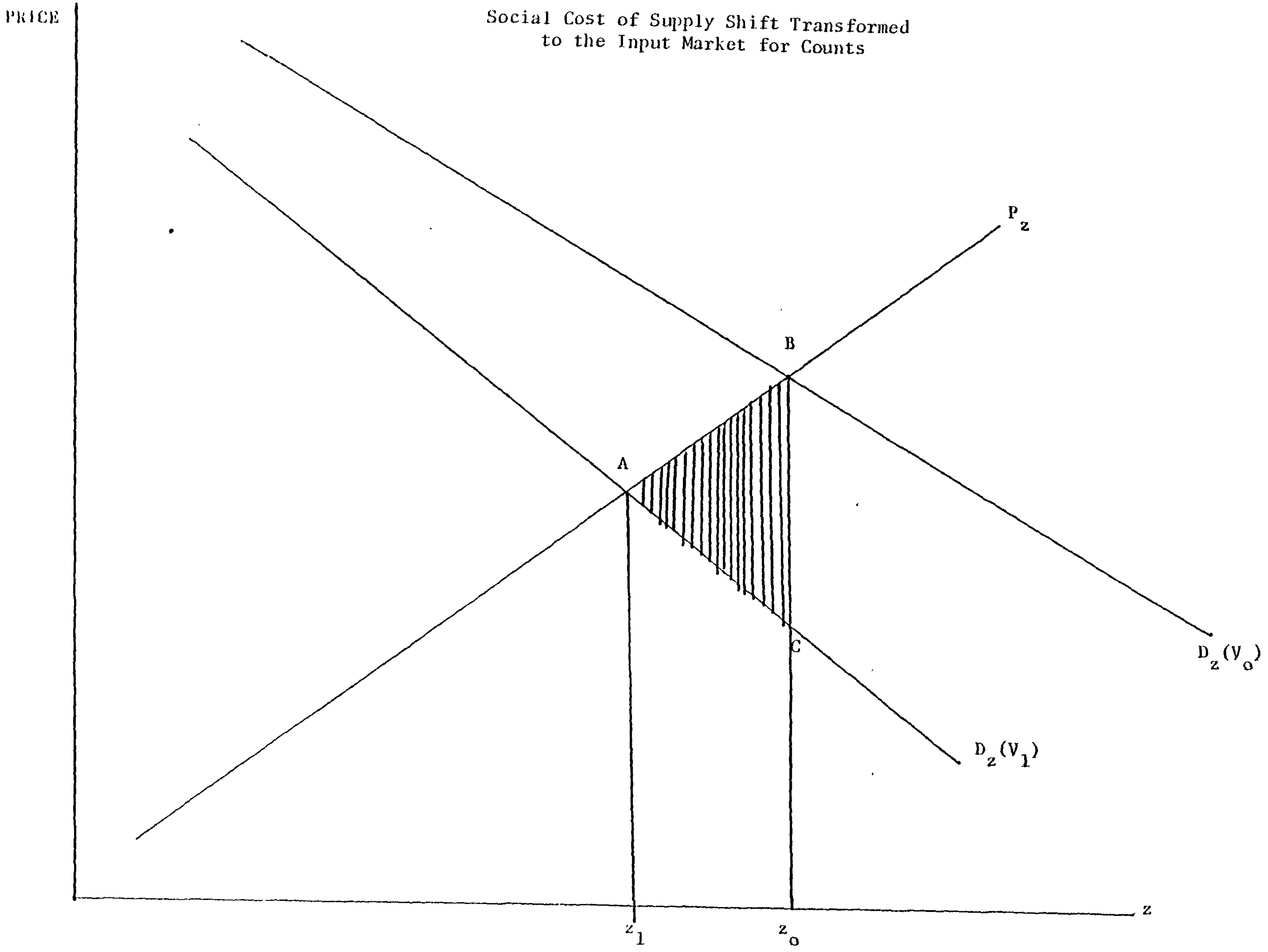
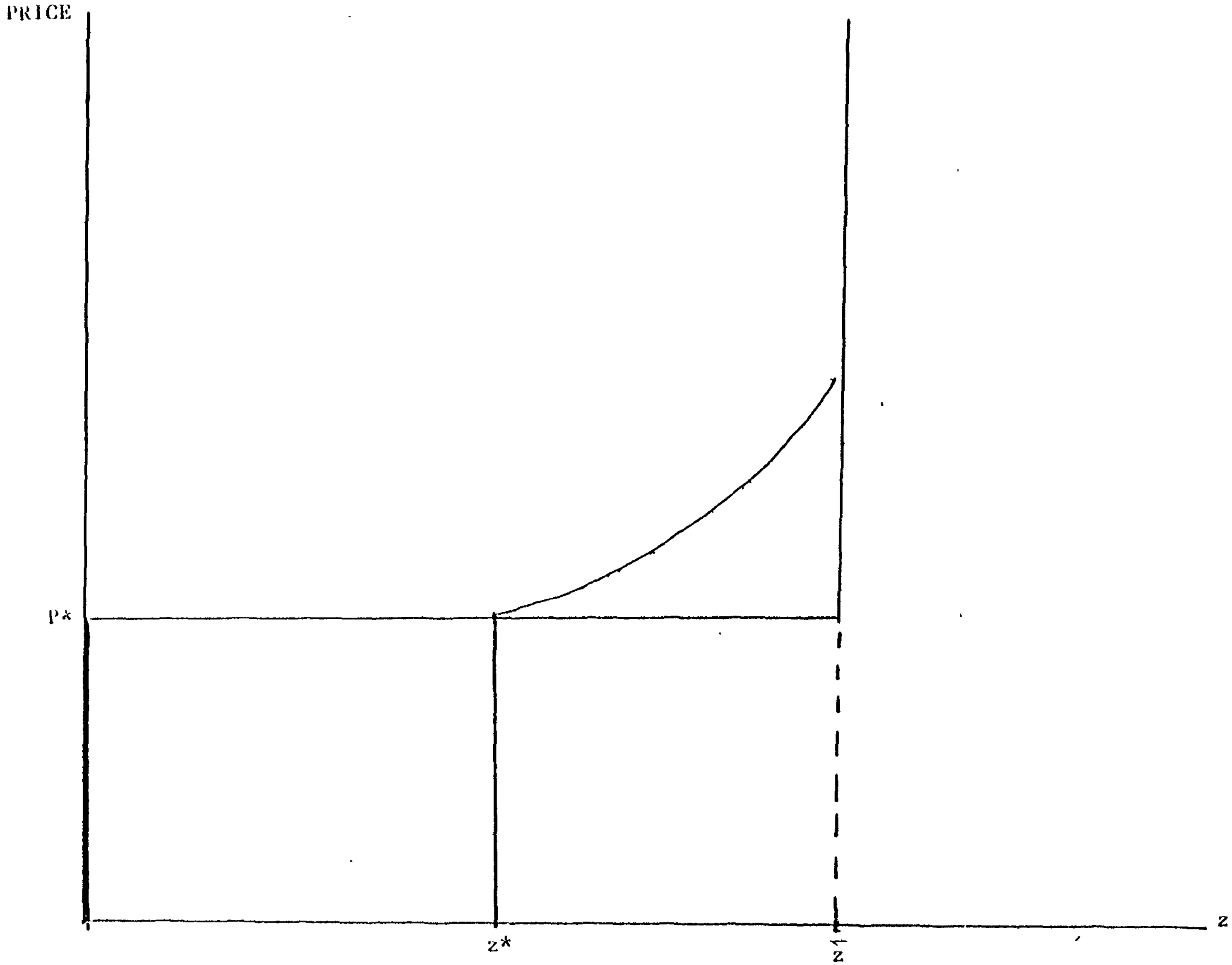


FIGURE 3-4

Supply Curve for Air Traffic Counts



and take-off delays. Thus, at some point z^*, the supply curve begins to slope upward reflecting this increased true cost. The effect of visibility changes is to shift z^* across the interval $(0,\bar{z})$ and thus shift the upward sloping portion of the supply curve.

The cost associated only with a shift in the supply of counts due to visibility changes is, as in the prior case of changes in costs of Y, the area between the two cost curves. Fig.3-5's shaded area is the cost associated with a shift of supply only. The complete cost is derived from a shift in the supply and demand for counts--which means combining the shaded areas.

Using the theoretical model constructed in the previous section, a framework for estimation can be developed. Consider the simple structural model below.

$$C^D_{it} = \alpha_o + \alpha_1 P^D_{it} + \alpha_2 V_{it} + \underline{\beta X}_{it} \tag{3-22}$$

$$C^S_{it} = \gamma_o + \gamma_1 P^S_{it} + \gamma_2 V_{it} + \underline{\delta X}_{it} \tag{3-23}$$

FIGURE 3-5

Cost Associated with a Supply Shift Only

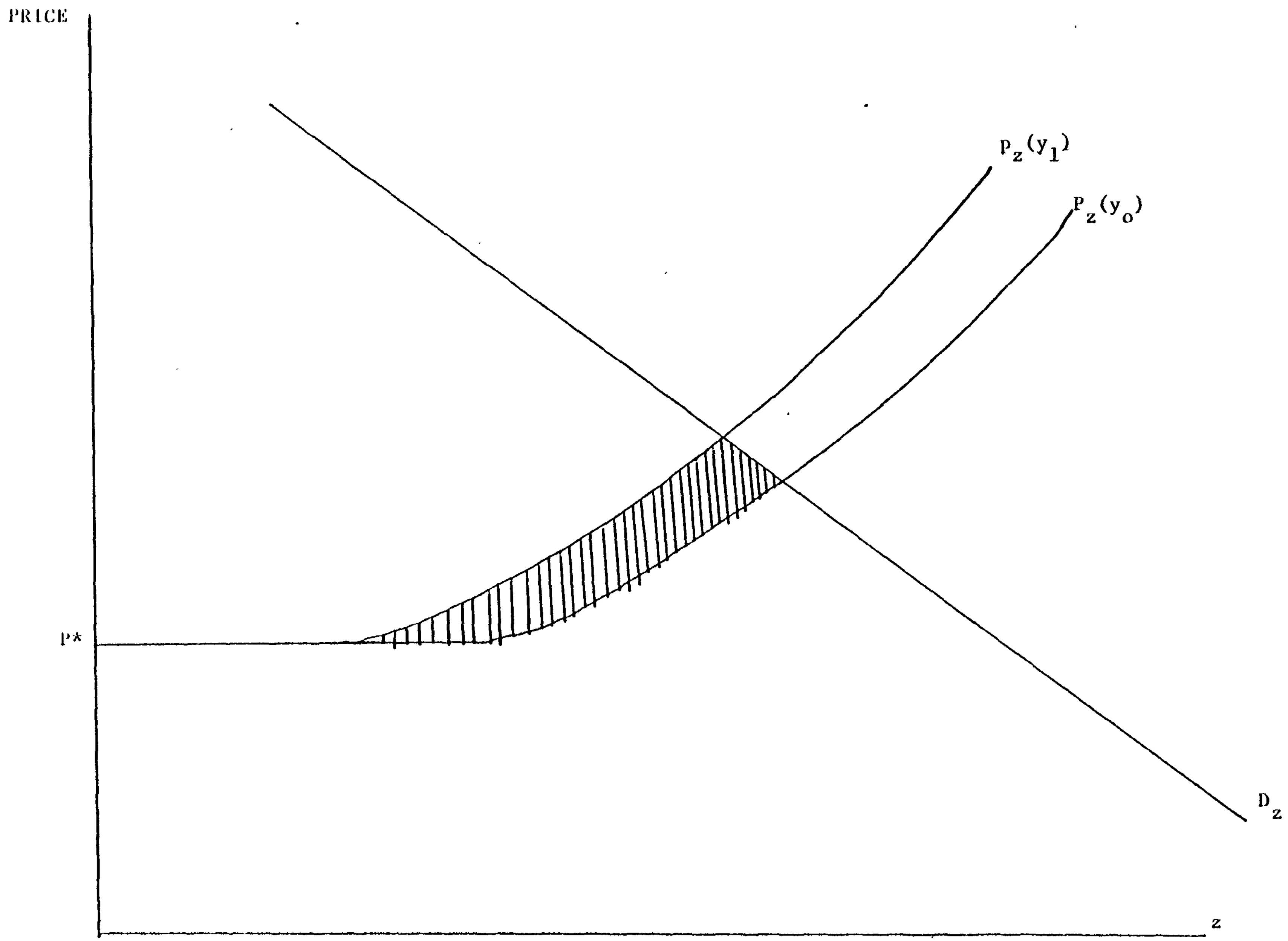
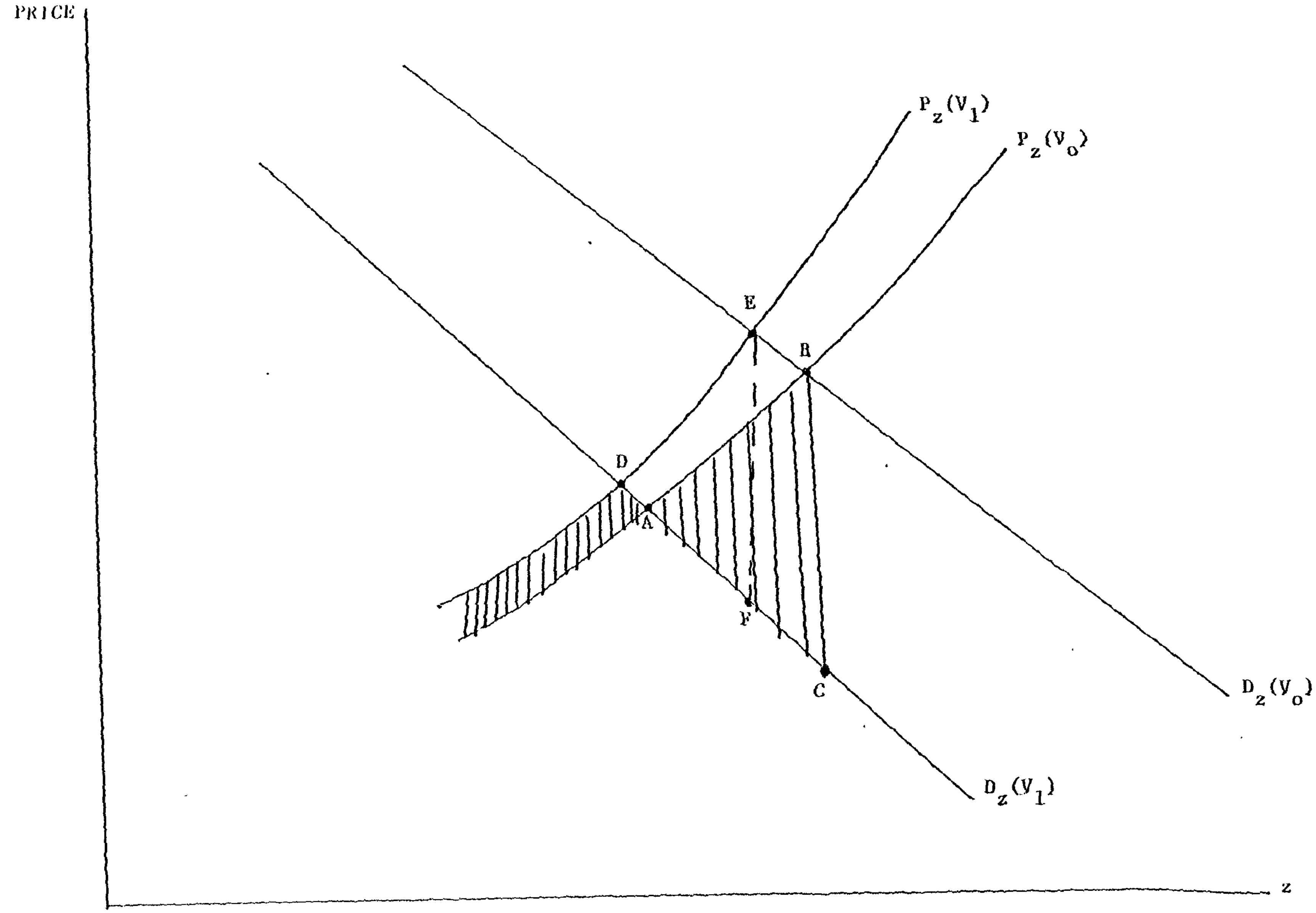


FIGURE 3-6

Social Cost Associated with Demand and Supply Shifts due to Visibility Variation



Eq. (3-22) is the demand curve for counts. Counts demanded are specified as a function of landing fee and time costs (P^D_{it}), visibility (V_{it}), and a vector of other weather - related variables ($\underline{X}_{it}$) at airport i for time t. Counts supplied are also expected to be a different function of the same variables. Some of these parameters can be signed _a priori_. α_1 is expected to be negative since an increase in price decreases demand. α_2 expected to be positive since visibility decreases lower counts demanded by increasing time costs. γ_1 is the standard positive effect in supply of price increases. γ_2 is expected to be positive since decreases in visibility decreases the amount of counts supplied.

The reduced form equation for counts is

$$(3\text{-}24)\quad C_{it} = \frac{1}{\alpha_1-\gamma_1}\left[\left(\frac{\alpha_o}{\alpha_1} - \frac{\gamma_o}{\gamma 1}\right) + \left(\frac{\alpha_2}{\alpha_1} - \frac{\gamma_2}{\gamma_1}\right)V_{it} + \left(\frac{\underline{\beta}}{\alpha_1} - \frac{\underline{-\delta}}{\gamma_1}\right)\underline{X}\right].$$

The reduced form parameter associated with visibility, $\left(\frac{1}{\alpha_1-\gamma_1}\right)\left(\frac{\alpha_2}{\alpha_1} - \frac{\gamma_2}{\gamma_1}\right)$, is expected to be positive in sign, but the underlying structural parameters are unidentified. By making some assumptions about relative magnitudes of α_1 and γ_1, a range of values for α_2, γ_2 can be established for the cost-benefit analysis discussed in the previous section.

Ta.3-17 presents the results from a regression of total daily traffic counts at Aurora Airport on a vector of weather variables. Ta.3-18 defines each of the regression variables. All continuous variables are in logarithm. One drawback of the data is that weather conditions are available only for O'Hare

TABLE 3-17

Classical Least Squares Regression Estimates
of Total Traffic Counts for Aurora Airport

DEPENDENT VARIABLE: LTOTO

SSE	374.402890	F RATION	2279.71
DFE	645.	PROB > F	0.0001
MSE	0.580470	R SQUARE	0.9815

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T-RATIO	PROB > T
LVIS	1	0.413987	0.077050	5.3730	0.0001
LCL	1	-0.104677	0.044098	-2.3737	0.0179
LWS	1	-0.282124	0.085868	-3.2856	0.0011
LWD	1	0.006086538	0.037512	0.1623	0.8712
RA	1	-0.00882506	0.001742717	-5.0640	0.0001
SN	1	-0.00699878	0.001800427	-3.8873	0.0001
FG	1	-0.014861	0.001654214	-8.4838	0.0001
LTEM	1	0.398944	0.050810	7.8517	0.0001
M	1	3.923506	0.570428	6.8782	0.0001
T	1	3.994875	0.560049	7.1331	0.0001
W	1	4.033440	0.566187	7.1239	0.0001
R	1	4.077325	0.559592	7.2862	0.0001
F	1	4.125296	0.571374	7.2200	0.0001
S	1	3.862951	0.571230	6.7625	0.0001
SU	1	3.739265	0.568384	6.5788	0.0001

TABLE 3-18

Regression Variable Definitions

LVIS	Visibility at O'Hare International Airport (in Logarithms)
LCL	Ceiling at O'Hare International Airport (in Logarithms)
LWS	Wind Speed at O'Hare International Airport (in Logarithms)
LWD	Wind Direction at O'Hare International Airport (in Logarithms)
RA	Discrete Variable indicating presence of rain at O'Hare
SN	Discrete Variable indicating presence of snow at O'Hare
FG	Discrete Variable indicating presence of fog at O'Hare
LTEM	Temperature in degrees Fahrenheit at O'Hare (in Logarithms)
M	Monday dummy for day of week effects
T	Tuesday dummy for day of week effects
w	Wednesday dummy for day of week effects
R	Thursday dummy for day of week effects
F	Friday dummy for day of week effects
S	Saturday dummy for day of week effects
SU	Sunday dummy for day of week effects

International Airport. Thus, to the extent that weather conditions vary across airports, this analysis will be in error. However, all airports fall within a 20 mile radius of the Chicago Loop area, so major weather changes are unlikely. Landing fees over the sample are also unavilable. The regression equation estimate is

$$C_{it} = \alpha_o + \alpha_1 LVIS_t + \alpha_2 LCL_t + \alpha_3 LWS_t + \alpha_4 LWD_t + \alpha_5 RA_t + \alpha_6 SN_t + \alpha_7 FG_t + \alpha_8 LTEM_t + \underline{\beta}\, \underline{D}_t + \varepsilon_t \quad , \tag{3-25}$$

where $\underline{D}_t$ is a vector of day of week dummies and ε_t is the white noise error term. The high value of the F-statistic and R-squared in Table 3 inidcates that the regression has high explanatory power over the sample. The visibility parameter is positive, as expected and quite precisely estimated. All parameters are of the expected sign except for that associated with LCL. The negative value indicates that as the ceiling increases, traffic counts fall. Wind direction effects are small and imprecisely estimated. However, it is included in the regression to capture differential runway capacity effects at multiple runway airports.

Ta.3-19 presents the estimates for DuPage County Airport. Again, the visibility coefficient is positive in sign and precisely estimated. Its value of .392 is quite close to the visibility coefficient at Aurora of .413. The negative effect of ceiling height again occurs, and the effect of wind direction is larger than at Aurora but is imprecisely estimated. The high F-statistic and R-squared values again indicate a good fit.

TABLE 3-19

Classical Least Squares Regression Estimates
of Total Traffic Counts at DuPage County Airport

DEPENDENT VARIABLE: LTOTO

SSE	90.172072	F PATIO	3270.19
DFE	319.	PROB > F	0.0001
MSE	0.282671	R-SQUARE	0.9935

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T-RATIO	PROB > T
LVIS	1	0.391728	0.076608	5.1134	0.0001
LCL	1	-0.104518	0.043144	-2.4225	0.0160
LWS	1	-0.485604	0.084391	-5.7542	0.0001
LWD	1	-0.037855	0.036887	-1.0263	0.3055
RA	1	-0.00582789	0.001709277	-3.4096	0.0007
SN	1	-0.012183	0.001735787	-7.0189	0.0001
FG	1	-0.012260	0.001619163	-7.5715	0.0001
LTEM	1	0.299262	0.049938	5.9927	0.0001
M	1	6.328694	0.562298	11.2550	0.0001
T	1	6.443391	0.551889	11.6751	0.0001
W	1	6.393385	0.557940	11.4589	0.0001
R	1	6.498858	0.5500934	11.7961	0.0001
F	1	6.499807	0.562287	11.5596	0.001
S	1	6.615916	0.563341	11.7441	0.0001
SU	1	6.526664	0.560167	11.6513	0.001

Ta.3-20 reports the regression coefficients for Chicago's Meigs Field. The visibility effect is positive as before, but is smaller at .25 than the other airports where it was around .4. Ceiling effects are still negative, but wind direction effects, while small, are more precisely estimated than at other airports. Again, all other signs are as expected.

This section has reported on the estimated effects of visibility for three airports in the Chicago area. All of the regression equations have very good explanatory power as indicated by their R^2 and F-statistic values. Visibility effects are strongly positive, and precisely estimated at all sites. The next section attempts to bound the range of supply and demand elasticities of visibility by referring to the structural model presented at the beginning of the section.

As eq.3-24 showed, the parameter associated with visibility in the reduced form regressions is an amalgam of prior elasticities and the true underlying elasticities of visibility. This section examines the values of these visibilities under several polar assumptions in order to determine a reasonable range for the true visibility elasticities.

Ta.3-21 presents the values of α_2, the demand elasticity of visibility, and γ_2, the supply elasticity of visibility at the three airports under alternative assumptions about the relative price elasticities. As Ta.3-21 shows, if the demand and supply curves are unitary price elastic or price inelastic, then the visibility elasticities are on the order of .4 or below. That is, a one percent decrease in visibility would yield at most a .4

TABLE 3-20

Classical Least Squares Regression Results of
Total Traffic Counts for Meigs Field

DEPENDENT VARIABLE: LTOTO

SSE	127.117252	F RATIO	1491.54
DFE	316.	Prob > F	0.0001
MSE	0.402270	R-SQUARE	0.9861

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T-RATIO	PROB > T
LVIS	1	0.250323	0.089207	2 8061	0.0053
LCL	1	-0.096790	0.051904	-1.8648	0.0631
LWS	1	-0.055751	0.100681	-0.5537	0.5801
LWD	1	0.063096	0.044101	1.4307	0.1535
RA	1	-0.00825438	0.002051089	-4.0244	0.0001
SN	L	-0.00495015	0.002105944	-2.3506	0.0194
FG	1	-0.012995	0.00194284	-6.6889	0.0001
LTEM	1	0.273146	0.059633	4.5805	0.0001
M	1	3.716479	0.671756	5.5325	0.0001
T	1	3.866213	0.659868	5.8591	0.0001
W	1	3.885791	0.667383	5.8224	0.0001
R	1	3.835062	0.659811	5.8124	0.0001
F	1	3.930859	0.673699	5.8347	0.0001
S	1	3.274191	0.672222	4.8707	0.0001
SU	1	3.159501	0.669603	4.7185	0.0001

TABLE 3-21

Sensitivity of Visibility Elasticity
Estimates to Price Elasticity Assumptions

	PRICE ELASTICITY ASSUMPTIONS					
AIRPORT	$\alpha_2 = \gamma_2$ $\alpha_1 = -.1$ $\gamma_1 = .2$	$\gamma_2 = 2\alpha_2$ $\alpha_1 = -.1$ $\gamma_1 = .2$	$\alpha_2 = \gamma_2$ $\alpha_1 = -.1$ $\gamma_1 = -.9$	$\gamma_2 = 2\alpha_2$ $\alpha_1 = -1$ $\gamma_1 = 1.9$	$\gamma_2 = \alpha_2$ $\alpha_1 = -10$ $\gamma_1 = 11$	$\gamma_2 = 2\alpha_2$ $\alpha_1 = -10$ $\gamma_1 = 11$
AURORA	α_2=.083 γ_2=.083	α_2=.05 γ_2=.1	α_2=.4 γ_2=.4	α_2=.25 γ_2=.5	α_2=45.5 γ_2=45.5	α_2=29.89 γ_2=59.77
DUPAGE	α_2=.08 γ_2=.08	α_2=.05 γ_2=.1	α_2=.35 γ_2=.35	α_2=.24 γ_2=.48	α_2=43.12 γ_2=43.12	α_2=28.3 γ_2=56.6
MEIGS	α_2=.05 γ_2=.05	α_2=.03 γ_2=.06	α_2=.23 γ_2=.23	α_2=.15 γ_2=.30	α_2=27.5 γ_2=27.5	α_2=18.0 γ_2=36.0

percent decrease in traffic counts demanded or supplied. However, if price elasticities are very large in absolute value, then the visibility elasticities are also quite large. For the type of traffic at these airports, one would expect to find a price elasticity which was quite small, thus implying small visibility effects. However, notice that by eq. 3-24, whatever the price elasticity is, given these results, visibility effects will be large in absolute value.

3.5.3 Visibility and Traffic Accidents

The automobile has become a way of life in industrialized societies, and closely associated with this fact is the annual increase in reported highway casualties in the major cities. The Department of Transportation (1981) reports there were 45,212 fatal accidents and 51,083 fatalities due to roadway usage in the U.S. in 1979. The number of motor vehicles involved was 64,754 and the accident rate was 3.35 fatalities per 100 million vehicle miles. For Illinois there were 2,017 fatalities and the accidnet rate was 3.2.

The number of accidents is affected by those factors which determine travel demand and travel behavior as well as by driving conditions. Several studies of traffic accidents exist which consider accidents to be the result of the demand and supply of motor vehicle travel under various conditions. Peltzman (1975) developed a model of driver behavior and analyzed fatal accident rates to estimate the impact of national highway safety policy in the U.S. The time series analysis of national data covered the period 1937-1972 and his cross-section analysis of state data covered 1962, 1965, 1967, and 1970. He explicitly recognized drivers' utility maximizing use of safety inputs including those supplied exogenously. Peltzman incorporated into his study the earlier research by safety scientists who focused almost exclusively on driving conditions for the effect of traffic density and the like. Ghosh, Lees, and Seal (1975) modeled drivers as trading off safety and low fuel consumption rates for savings of time in choosing their utility maximizing speed of travel. As part of their analysis they estimated a production function for casualties on British motorways using monthly data for the period January1972 to March 1974. The evidence indicates that relevant factors include driver characteristics and driving conditions including weather.

In addition to the research which centers on driver behavior, there is considerable research on the contributions of vehicle and roadway design, and driving conditions to traffic accidents. In Blomquist (1977), a search to identify factors affecting seat-belt productivity found that vehicle speed, alcohol consumption, week-end and night driving, small cars, and high-speed travel on non-interstate highways each tend to increase the probability of a fatal accident.

Fatal Accident Reporting System 1979 gives facts and figures which quantify the gross (as opposed to partial) effects of these and other factors on the number of fatal accidnets. One of the relevant characteristics of the 1979 fatality profile is that an overwhelming majority of fatalities occured during clear weather conditions. According to the Department of Transportation (1981), only fourteen percent of the fatalities were associated with inclement conditions. With rain-slick or ice-slick roads being the worst weather conditions, one would not expect atmospheric visibility to be dominant. However, it is identifiable and measurable.

Measuring the benefits of better visibility can be accomplished by: (1) estimating the physical damage caused by poor visibility, and (2) placing a dollar value on that damage. Our analyses showed that while improvements in visibility lead to decreases in nonfatal accidents, it also resulted in an increase in the probability of fatal accidents. It was also found that a unit improvement in visibility resulted in cost saving of 9.45 million dollars (1980 prices).

In this study we examine the effects of weather (rain, snow, ice, fog), visual range (visibility) and the seasonal variables on highway accidents in Cook and DuPage counties in the Chicago SMSA. The data utilized in the analysis covered the period from January 1978 to June 1980 and the highway casualties are classified into two categories: fatal and non-fatal accidents. First is provided a theoretical examination of the effects of visibility on traffic accidents based on the assumption that travel cost minimization is the main driving force behind the choice of vehicles, speed, direction of travel or route in making a trip between given destinations. It is shown that while the partial effect of improvements in visibility on highway accidents is positive, the total effect is ambiguous. Next are provided some econometric estimates of the relationships between highway accidents - fatal as well as non-fatal - and visibility, weather conditions and seasonal variables for Cook and DuPage counties. It is important to note that only one dimension of benefits from visibility improvements has been estimated--reduction in traffic accidents. Other important benefits, such as increases in speed and volume of traffic have not been addressed. Thus, the benefits estimated in this section represent a lower bound of visibility improvement benefits.

In this section, we attempt to find out whether there is an unambiguous relationship between improvements in visibility and accident rates, assuming that cost minimization is the major driving force behind drivers' travel decisions. Assume two urban communities of the same socio-economic characteristics, highway design conditions and population size. At first thought, most observers would agree that the community with very poor visibility conditions will be less safe (in terms of highway accident reductions) compared to the community with good visibility conditions, even thought poor visibility might lead to a slow down of speed and a decrease in the volume of traffic.

Let us define an improvement in safety as a change in climatic conditions, visibility, traffic volume, speed etc., which reduces the rate of traffic accidents. In this respect, we are more concerned with traffic volume, speed, environmental conditions and visibility, while holding vehicle designs, road conditions (e.g., potholes), highway design and other engineering characteristics of the highway constant. Economic efficiency requires that the cost of achieving a given level of safety be minimized. Let us assume that the consumer computes the price of travel as a solution to the problem of minimizing the cost of travel to his or her destination where the cost of travel is made up of vehicles operating cost and the cost of accidents (measured in terms of what consumers will be willing to pay to avoid accidents). The value of the motorists' time, although positive, is not explicitly included in the model. Let us further assume that decisions concerning choice of vehicle type and direction of travel have already been made by the motorist, Then the most relevant variable under the control of the motorist is speed. The motorist has no control over highway conditions such as traffic volume and the behavior of other motorists as well as the weather and visibility, but all these variables do affect his cost of travel. If we assume that the safety of a trip depends on speed, weather conditions, visibility, traffic volume for given highway design characteristics, mechanical conditions of the automobile, age of driver, blood alcohol level etc., then the accident rate AR = AR(VIS, RC, SP, TV, O) , where

VIS = visibility (e.g., visual range in miles) ,

RC = road conditions e.g., inches of rain, snow, ice etc.,

SP = speed,

TV = traffic volume in vehicle miles per highway mile,

O = other relevant variables.

For simplicity, let us assume that travel cost

(3-26a) $$TC = AC(sp)\ AR(VIS, RC, SP, TV, O) + OC(sp)\ ,$$

where AC(sp) = average cost per accident. It is assumed that accidents which occur at higher speeds are more costly in terms of the damages done to life and property than accidents which occur at lower speeds $\left(\frac{\partial AC(sp)}{\partial (sp)} > 0\right)$.

OC(sp) represents the operating cost per mile. This may include the value of the motorists' time. It is also assumed that, up to the relevant speed limit, the marginal cost of a vehicle mile decreases as speed increases,

Without considering other environmental variables and visibility conditions, the choice of speed to minimize travel cost, TC, requires that

(3-26b) $$\frac{dTC}{d(sp)} = AR\frac{\partial (AC)}{\partial (sp)} + AC\frac{\partial (AR)}{\partial (sp)} + \frac{\partial (OC)}{\partial (sp)} = 0\ ,$$

i.e.,

(3-26c) $$\left[AR\frac{\partial (AC)}{\partial (sp)} + AC\frac{\partial (AR)}{\partial (sp)}\right] = -\frac{\partial (OC)}{\partial (sp)}\ .$$

Eq. (3-26c) requires the motorist to equate the marginal increase in accident cost per mile (LHS) to the marginal savings in operating cost per mile. For the extreme point to be a minimum, the second derivative of the TC function, represented by Z, must be positive.

Our present task is to find the effect of improvement in visibility on accident rates. To obtain the solution to this problem, we totally differentiate the accident rate AR with respect to visibility,

From eq.(3-26a) the total effect of improvement in visibility on accident rates,

$$\text{(3-26d)} \quad \frac{dAR}{d(VIS)} = \underset{(+)}{\frac{\partial AR}{\partial(sp)}} \quad \frac{d(sp)}{d(VIS)} \quad + \underset{(-)}{\frac{\partial AR}{\partial(VIS)}} + \underset{(+)}{\frac{\partial AR}{\partial(TV)}} \cdot \frac{dTV}{d(VIS)} \; .$$

Let us assume that the partial effect of improvement in visibility on accident rates, $\frac{\partial AR}{\partial(VIS)}$, is negative and $\frac{\partial AR}{\partial(sp)}$, which measure the partial effect of speed on accident rates, is positive. The third term, $\frac{\partial AR}{\partial(TV)} \cdot \frac{dTV}{d(VIS)}$, measures the effect of visibility on accident rates through its influence on highway congestion, TV. The partial effect of highway congestion on AR, $\frac{\partial AR}{\partial(TV)}$, is assumed to be positive i.e., more accidents occur on congested urban highways than on rural highways. For simplicity, let us assume that the effect of visibility on traffic volume is small and positive. The total effect of improvement in visibility on accident rates then depends on $\frac{d(sp)}{d(VIS)}$ i.e., the total effect of improvement in visibility on speed.

Totally differentiating eq.(3-26b) holding RC,TV, and O constant. we obtain

$$\text{(3-26e)} \quad \frac{d(sp)}{d(VIS)} = -\left[\underset{(+)}{AC} \underset{(-)}{\frac{\partial^2 AR}{\partial(sp)\partial(VIS)}} + \underset{(+)}{\frac{\partial AC}{\partial(sp)}} \; \underset{(-)}{\frac{\partial AR}{\partial(VIS)}} \right] x \; Z^{-1} \quad ,$$

where Z represents the second derivative of cost per mile with respect to speed. This is positive.

The average cost of an accident, AC, is positive and $\frac{\partial^2 AR}{\partial(sp)\partial(VIS)}$, which measures the effect of an improvement in visibility on the rate at which accident rates change with respect to speed, is assumed to be negative, i.e., accidents are more likely to increase less, for given speeds, following improvements in visibility. Since accident costs are more likely to increase with speed, $\frac{\partial AC}{\partial (sp)}$ is positive, which makes the bracketed term in eq.(3-26d) negative. Thus $\frac{d(sp)}{d(VIS)}$ is positive i.e. improvements in visibility encourage higher speed levels,

Substituting $\frac{d(sp)}{d(VIS)} > 0$ into eq. (3-26d) the sign of $\frac{dAR}{d(VIS)}$, the total effect of an improvement in visibility on accident rates, becomes ambiguous.

3.5.4 Analysis of Highway Casualties in DuPage and Cook Counties

3.5.4.1 Empirical Analysis

Data on the number of fatal and non-fatal accidents have been collected for Cook and DuPage counties from January 1978 to June 1980 on daily basis. Visibility data, measured in terms of miles of visual range, have also been assembled from the O'Hare airport. In addition to the above information, weather data have also been collected from the O'Hare weather station on the occurence of snow, fog and rain as well as daily recording of the dry bulb temperature in degrees F. The data do not include information on traffic volume and speed in these two counties. Given the quality of data available, the best one can do is to attempt to estimate an econometric relationship between traffic accidents and visibility, weather and the day or season in which the accident occured. These relationships were estimated for DuPage and Cook counties for non-fatal and fatal accidents separately. The following general equation was estimated separately for both counties:

$$
\begin{aligned}
\text{(3-27a)} \quad Z_t = {} & \alpha_o + \alpha_1 DD_t + \alpha_2 WNTR_t + \alpha_3 SUMR_t + \alpha_4 SPR_t + \alpha_5 VIS_t + \alpha_6 VIS_t^2 \\
& + \alpha_7 DVD_t + \alpha_8 VWTR_t + \alpha_9 VSPR_t + \alpha_{10} VSUM_t + \alpha_{11} RA_t + \alpha_{12} SN_t + \alpha_{13} FG_t \\
& + \alpha_{14} VTEM_t + \alpha_{15} VRA_t + \alpha_{16} VSN_t + \alpha_{17} TEM_t + \varepsilon_t, \quad t=1,2......912
\end{aligned}
$$

Variables definitions are as follows:

Z_t = Number of non-fatal accidents per day in DuPage county (DPNONFAT) or Number of non-fatal accidents per day in Cook county (CKNONFAT),

DD equals 1 if the accident occured on weekends and equals 0 otherwise,

WNTR equals 1 in winter time and 0 otherwise,

SUMR equals 1 in spring and 0 otherwise,

VIS represents visibility measured in miles,

DVD represents the interaction between visibility and day of occurence of the accident, while VWTR, VSPR AND VSUM measure the interactions between visibility and the seasons (winter, spring and summer). RA equals 1 if there was an occurence of any of the following phenomena on the day the accident occured - rain, rain showers, freezing rain, rain squals, drizzle or freezing drizzle, and 0 otherwise. SN is a 1/0 dummy variable indicating the occurence/non-occurence of any of the following phenomena on the day the accident occured - snow, snow pellets, ice crystals, snow showers etc. FG is also a 1/0 dummy variable indicating the occurence/non-occurence of either fog, ice fog, ground fog, etc. TEM represents temperature in degrees F., while VTEM,VRA, VSN measure the effects of the interaction between temperature, rain and snow, respectively, on traffic accidents.

Ta.3-22 presents the results of a linear regression model for non-fatal accidents in DuPage county. The low R^2 obtained can be partly attributable to the absence of such variables as speed and traffic volume from the model. The parameter estimates indicate that the number of non-fatal accidents increases by almost 8 units per day on weekends compared to weekdays. The coefficient for

TABLE 3-22

DuPage County Non-Fatal Accidents Regression Results

	Dependent Variable: DPNONFAT	
VARIABLE	PARAMETER ESTIMATE	T RATIO
Intercept	69.088	8.065
DD	7.844	3.159
WNTR	15.187	3.154
SUMR	7.069	1.343
SPR	15.137	3.254
VIS	-3.445	-3.250
VIS^2	0.046	1.265
DVD	-0.064	-0.293
VWTR	0.907	2.123
VSPR	0.791	2.001
VSUM	0.424	0.955
RA	7.463	2.406
SN	13.451	3.621
FG	0.140	0.086
VTEM	0.022	2.133
VRA	0.086	0.242
VSN	-1.273	-2.86
TEM	-0.405	-3.49

PR > F = 0.0001

R^2 = 0.323

DW = 1.46

visibility shows that an improvement in visibility by one mile decreases the number of non-fatal accidents by 3.4 per day. This result is consistent with a priori expectations concerning the partial effects of an improvement in visibility on highway casualties. The results also show that seasonal coefficients for winter and spring are precisely estimated. The number of non-fatal accidents increases by 1.5 units per day in winter and spring compared to the base season (fall). But summer shows an increase of only 7 per day above the base season. The summer coefficient is, however, imprecisely estimated. The interactions between visibility improvement and the seasons show that a unit increase in visibility increases the number of non-fatal accidents by almost one unit per day each in winter and spring, while the coefficient of the interaction between visibility and SUMR is imprecisely estimated.

The sign of the coefficients for the weather variables are consistent with a priori expectations. The occurence of rain increases the number of non-fatal accidents by 7.5 per day while the presence of snow increases the number of non-fatal accidents by 13.5. Thus, the number of non-fatal accidents which occur in the presence of snow can be expected to exceed the non-fatal accident which occur in the rainy season. The coefficient for fog is, however, imprecisely estimated. An increase in temperature by 10 degrees F., decreases the number of non-fatalities in DuPage county by 4 per day. This is probably due to the fact that people are more likely to engage themselves in other outdoor activities when the temperature increases.

The interactions between visibility improvements and the weather variables for DuPage county indicate that, although the number of non-fatal accidents increases by 13.5 per day in the presence of snow, a unit improvement in visibility In the presence of snow decreases the number of non-fatal accidents by 1.3 per day. An improvement in visibility by one unit on a snowy weekend at an average winter temperature of 30°F can be computed for DuPage county by evaluating the following expression:

$$\text{(3-27b)} \quad \frac{\partial(\text{DPNONFAT})}{\partial(\text{VIS})} = -3.455 + 2\text{x}0.046\overline{\text{VIS}} - 0.064\text{DD} + .907\text{WNTR} + 0.022\overline{\text{TEM}} - 1.273\text{SN} \quad .$$

Eq.(3-27b) is obtained by taking the first derivative of the equation presented in Ta.3-22 with respect to visibility. Evaluating the expression obtained at SN=1, DD=1, WNTR=1, $\overline{\text{VIS}}$ = average visibility = 10.3 miles, $\overline{\text{TEM}}$ = average winter temperature = 30°F provides the required result, Ta.3-23 presents the average values of some of the variables used in the analysis. Substituting these values into eq.3-27b it is realized that a unit improvement in visibility on a snowy weekend leads to a decrease in the number of non-fatal accidents by 2.28 per day in DuPage county. The effect of an improvement in visibility on the number of non-fatal accidents occuring on a rainy day can also be obtained by evaluating the following expression at the average values of the variables:

$$\text{(3-27c)} \quad \frac{\partial(\text{DPNONFAT})}{\partial(\text{VIS})} = -3.445 + 2\text{x}0.046\overline{\text{VIS}} - 0.064\text{DD} + 0.022\overline{\text{TEM}} + 0.086\text{RA} \quad .$$

Inserting the relevant average values of the variables into eq.(3-27c) shows that on a rainy weekend, a unit improvement in visibility leads to a decrease in the number of non-fatal accidents by 1.35 per day, compared to a decrease of 1.28 on a rainy weekday.

TABLE 3-23

Statistics on Some Variables
Included in the Regression Analysis

VARIABLE*	NUMBER OF OBSERVATIONS	MEAN	MINIMUM VALUE	MAXIMUM VALUE	RANGE
DPNONFAT	1035	28.98341	5.00000	118.00000	113.00000
CKNONFAT	1035	194.29372	72.00000	729.00000	657.00000
CKFATAL	1035	0.41836	0.00000	1.00000	1.00000
DPFATAL	1035	0.10725	0.00000	1.00000	1.00000
SN	912	0.11952	0.00000	1.00000	1.00000
TEM	912	51.27412	-8.33333	89.33333	97.66667
VLS	912	10.31060	0.31250	16.66667	16.35417

*VARIABLE DEFINITIONS:

DPNONFAT = Number of non-fatal accidents in DuPage County
CKNONFAT = Number of non-fatal accidents in Cook County
CKFATAL = Number of fatal accidents in Cook County
DPFATAL = Number of fatal accidents in DuPage County
SN = Snow (dummy variable)
TEM = Temperature (°F)
VIS = Visibility in miles

Ta.3-24 presents the non-fatal accidents regression results for Cook Country. By comparison with Ta.3-22, almost all the coefficients have the same signs as obtained from the DuPage County regression results, except the FG coefficient. In Cook County, the presence of fog decreases the number of non-fatal accidents by 10.9 while it virtually has no effect in DuPage County. The magnitudes of the effects the explanatory variables in the Cook County regression results exceed those obtained for DuPage County.

In Cook County the number of non-fatal accidents increases by 48 at weekends compared to weekdays. All the seasonal coefficients are precisely estimated except the coefficient for summer. The results show that the number of non-fatal accidents increases by 60 per day in winter compared to fall. During the spring season, non-fatal accidents increase by 56.72 per day compared to fall base season. As in DuPage County, a one mile improvement in visibility in Cook County leads to a reduction in the number of non-fatal accidents but the decrease is almost by 16 per day compared to 3 per day for DuPage County. This effect does not include the interaction terms of visibility and the other variables. The coefficients of the weather variables also show that the number of non-fatal accidents increases by 46.7 per day in the presence of rain while the effect of an occurence of snow increases the number of non-fatal accidents by 63 per day in Cook County.

Considering the interaction terms between visibility and the other explanatory variables, an improvement in visibility by one mile on a snowy weekend or weekday at an average winter temperature of about 30°F can be computed by evaluating the following expression:

TABLE 3-24

Cook County Non-Fatal Accidents Regression Results

VARIABLE	PARAMETER ESTIMATE	T RATIO
	Dependent Variable: CKNONFAT	
Intercept	387.55	9.47
DD	48.27	4.18
WNTR	60.37	2.48
SUMR	22.77	0.87
SPR	56.72	2.44
VIS	-15.63	-3.25
VIS^2	0.026	0.16
DVD	-0.72	-0.71
VWTR	4.82	2.36
VSPR	2.96	1.57
VSUM	2.17	1.02
RA	46.73	3.33
SN	63.15	3.84
FG	-10.88	-1.15
VTEM	0.148	3.06
VRA	-0.027	-0.02
VSN	-4.11	-2.07
TEM	-2.35	-4.17

PR > F = 0.0001

R^2 = 0.35

DW = 1.39

$$\text{(3-27d)} \qquad \frac{\partial(\text{CKNONFAT})}{\partial(\text{VIS})} = -15.63 + 2(0.026)\overline{\text{VIS}} - 0.72\text{DD} + 4.82\text{WNTR} + 0.148\overline{\text{TEM}} - 4.11\text{SN} \; .$$

Eq.(3-27d) is obtained by taking the first derivative of the regression equation presented in Ta.3-24 with respect to visibility. An evaluation of eq.(3-27d) at the mean values of the relevant variables and an average winter temperature of 30°F shows that an improvement in visibility by one mile on a snowy weekend leads to a decrease in the number of non-fatal accidents by 10.7 per day. It is observed from Ta.3-24 that the effect of an improvement in visibility alone, without considering the interaction terms, is to decrease the number of non-fatal accidents by about 15 per day. But when the interaction terms are considered, the effect of the interaction between an improvement in visibility and winter season is to increase the number of non-fatal accidents in Cook County by 4.82 per day.

The effect of an improvement in visibility on the number of non-fatal accidents occuring on a rainy day can be computed by evaluating the following expression at the average values of the relevant variables:

$$\text{(3-27e)} \qquad \frac{\partial(\text{CKNONFAT})}{\partial(\text{VIS})} = -15.63 + 2(0.026)\overline{\text{VIS}} - 0.72\text{DD} + 0.148\overline{\text{TEM}} - 0.027\text{RA} \; .$$

Inserting the relevant average values of the variables into eq.(3-27e) shows that on a rainy weekend, an improvement in visibility by one mile leads to a decrease in the number of non-fatal accidents by 8.3 per day.

3.5.4.2 Linear Probability Models of Traffic Fatalities

The average number of non-fatal accidents reported for DuPage County during the period for which the accident data were collected was 28.98. while the average for Cook County was 194.3 non-fatal accidents per day. Very few fatalities were recorded. In fact an average of 0.42 fatalities Per day was recorded for Cook County compared to an average of 0.11 fatalities per day for DuPage County. This means that most of the elements under the dependent variable column in the regression model are zeroes and ones. Very few fatal accidents greater than one were recorded for both counties. Therefore, it was decided to use a qualitative choice model in which the dependent variable is 0 when the accident is non-fatal and 1 when the accident was fatal.

The simplest specification of a qualitative choice model is the linear probability model, where it is assumed for the purpose of this analysis that the probability of occurence or non-occurence of a fatal accident on any given day is a linear function of the explanatory variables listed in Ta.3-22 and 3-24.

Let
$$\begin{aligned} FATAL_t = {} & \alpha_o + \alpha_1 DD_t + \alpha_2 WNTR_t + \alpha_3 SUMR_t + \alpha_4 SPR_t + \alpha_5 VIS_t \\ & + \alpha_6 DVD_t + \alpha_7 VWNTR_t + \alpha_8 VSPR_t + \alpha_9 VSUM_t + \alpha_{10} RA_t \\ & + \alpha_{11} SN_t + \alpha_{12} FG_t + \alpha_{13} VTEM_t + \alpha_{14} VRA_t + \alpha_{15} VSN_t \\ & + \alpha_{16} TEM_t + \varepsilon_t \quad . \end{aligned}$$

For DuPage County,
$$FATAL_t = DPFATAL_t = \begin{cases} 1, & \text{if fatal accident was recorded.} \\ 0, & \text{otherwise} \end{cases}$$

For Cook County, $FATAL_t = CKFATAL_t = \begin{cases} 1, & \text{if fatal accident was recorded} \\ 0, & \text{otherwise} \end{cases}$

Thus, the regression coefficients may be interpreted as the effects of unit changes in the explanatory variables on the probability of occurence of fatal accidents. The above model was estimated by Ordinary Least-Squares procedure for DuPage and Cook Counties and the results are presented in Ta.3-25. The very low R^2 suggests that a good deal of variance in the model is unexplained. Nonetheless, it is our belief that, with the availability of data on relevant variables such as vehicle speed and traffic volume, there would be an improvement in the fit of the Linear Probability Model.

The results show that an improvement in visibility by one mile leads to an increase in the probability of fatalities by 0.005 in DuPage County, compared to an increase of 0.02 in Cook County. This result does not include the interactions between visibility and the other explanatory variables. If we consider the interaction between visibility and the day of week effect (DVD), an improvement in visibility leads to an increase in the probability of fatalities by 0.009 in Cook County and a decrease in the probability of fatalities by 0.014 in DuPage County during the weekends. The DuPage County estimate of the interaction between visibility and the day of week effect is, however, more precisely estimated than the Cook County estimate. The effect of the interaction between visibility and the seasons is to decrease the probability of occurence of fatalities in winter and spring in Cook County by 0.022 and 0.020 respectively. An improvement in visibility in summer time leads to an increase in the probability of occurence of fatal accidents by 0.003 in Cook County.

TABLE 3-25

Linear Probability Models of Traffic Fatalities in Cook and DuPage Counties

	Cook County Results		DuPage County Results	
VARIABLE	PARAMETER ESTIMATE	T RATIO	PARAMETER ESTIMATE	T RATIO
Intercept	-0.059	-0.215	0.095	0.545
DD	0.026	0.289	0.137	2.372
WNTR	0.258	1.473	-0.037	-0.334
SUMR	-0.062	-0.319	0.000	0.002
SPR	0.180	1.041	0.049	0.447
VIS	0.023	0.979	0.005	0.318
DVD	0.009	1.080	-0.014	-2.688
VWTR	-0.022	-1.417	-0.002	-0.166
VSPR	-0.020	-1.353	-0.007	-0.764
VSUM	0.003	0.181	-0.002	-0.176
RA	0.008	0.075	-0.001	-0.016
SN	0.037	0.289	0.026	-0.331
FG	-0.047	-0.801	0.0363	0.977
VTEM	-0.0002	-0.659	0.000	0.112
VRA	-0.02	-0.147	-0.007	-0.865
VSN	0.004	0.250	0.006	0.593
TEM	0.006	1.534	-0.0004	-0.147

Cook County	DuPage County
PR > F = 0.0059	PR > F = 0.5997
R^2 = 9.0367	R^2 = 0.0154
DW = 1.932	DW = 2.098

The coefficients of the interaction terms between visibility and winter, and spring (VSPR) are more precisely estimated than the summer interaction term in the Cook County model. The DuPage County results show that the effect of interactions between visibility and the seasons is to decrease the probability of occurrence of fatal accidents, but these coefficients are imprecisely estimated.

3.5.4.3 Monetary Value of Benefits

The results of the Cook County linear probability model parameter estimates for the occurrence of fatal accidents shows that an improvement in visibility by one mile increased the probability of occurrence of daily accidents by 0.023. The daily fatal accidents rate for Cook County is 0.42. Thus the expected number of fatal accidents occurring in Cook County per day due to a mile improvement is 0.01. This represents 3.65 traffic fatalities per annum. The loss in human lives represents a cost to society, largely resulting from risks voluntarily incurred. This cost partly offsets the gains obtained by the great majority of motorists because of time saved. Ignoring the net affects of traffic fatalities contributes to a conservative estimate of the benefits of improved visibility. Professor Sherwin Rosen's risk-compensating wage differential estimates (1976) produce an average statistical value of life of 494,000 dollars (1980). The 3.65 traffic fatalities which occur due to an improvement in visibility by one mile in Cook County represents a cost of 1.80 million dollars (1980) in human life. A simple linear extrapolation of this value to cover the entire eastern United States yields a benefit of 204 million (1980) dollars.

In valuing the reduction in nonfatal accidents we make use of the nonfatal injury costs estimated by Faigan (1975) and the Proceedings. Ta. 3-26 presents the breakdown of the injury costs in 1972 dollars. The average nonfatal injury loss which can be aboided is $3000 per accident in 1972 dollars. Using the estimate of the annual reduction in traffic accidents due to a one mile improvement in visibility, a rough estimate of the annual benefits from a one mile improvement in visibility is 17 million dollars in Cook County. This translates into 35 million 1980 dollars, using the 1980 consumer index. A simple linear extrapolation to the entire U.S. yields an annual benefit of about $750 million (1980).

TABLE 3-26

Non-Fatal Injury Accident Costs*

TYPE OF COST	COST IN 1972 DOLLARS
Labor Productivity Low	850
Medical	350
Pain and Suffering	100
Property Damage	700
Legal	150
InsuranceAdministration	800
Other	50
Total	3000

*Source: G. Blomquist "Value of Life: Implications of Automobile Seat Belt Use" p. 47

3.5.5 Summary and Conclusions

A conceptual model of the relationship between travel cost, accident rates, weather conditions, improvement in visibility, vehicle speed, and traffic congestion has been developed. Based on the assumption that travel cost minimization is the main driving force behind drivers' choice of vehicle speed and direction of travel when vehicle and highway designs, road conditions and other engineering characteristics of highways are held constant, it is shown that the total effect of an improvement in visibility on accident rates depends crucially on the effect of improvements in visibility on vehicle speed. It has been demonstrated that improvements in visibility encourage higher speed levels, for a given traffic volume and road condition, thus leading to the conclusion that the total effect of improvements in visibility on traffic casualties is ambiguous.

The empirical estimations of the relationship between improvements in visibility, weather variables and traffic casualties show that visibility improvements lead to significant reductions in non-fatal accidents in both Cook and DuPage Counties. This result is consistent with the partial effect of improvements in visibility on highway casualties. While the occurence of rain and/or snow lead to an increase in the number of non-fatal accidents in Cook and DuPage Counties, the empirical results also show that an improvement in visibility in the presence of snow leads to a decrease in the number of non-fatal accidents in both counties. Empirical estimates of benefits from increased speed and traffic volume have not been made.

Results of linear probability models in analyzing the traffic fatalities show that an improvement in visibility during the weekends leads to an increase in the probability of occurrence of fatal accidents in Cook and DuPage Counties. Visibility improvements in winter and spring, however, lead to decreases in the probability of occurrence of fatal accidents in both counties, although these coefficients are not very precisely estimated. An improvement in visibility in Cook County by one mile leads to an estimated benefit of 35 million dollars as a result of reductions in traffic casualties. This translates into an annual benefit of about $750 million for the entire eastern U.S.

3.6 Effects of a One Mile Change in Visibility: Comparisons of Willingness to Pay and Secondary Data Results

Estimated willingness to pay for a uniform one mile visibility improvement in the eastern U.S. is given in Ta.3-27. The one mile improvement scenario is suitable for comparison with benefits derived from analyses of secondary data. Scenario benefits in Ta.3-27 are derived from the six-city eastern survey, using the visibility value function from section 2 aggregates according to the method explained in section 4. Aggregate 1990 benefits are about $10 billion for the hypothetical argument on visibility of one mile. It should be emphasized that tje one mile improvement does not refer to any real program and is used here only for purposes of comparing the contingent valuation and secondary ratio estimates.

Reduction of nonfatal traffic accidents is responsible for the largest visibility improvement benefit among the Project's secondary data analyses. Based upon the Cook County, Illinois results, eastern U.S. benefits from a one mile uniform visibility improvement would be about 0.75 billion in 1980 dollars. The $10 billion aggregate benefit reported in Ta.3-27 comprises all visibility benefits, whether they be aesthetic, safety-related or derived from a multitude of other goods to which visibility contributes.

TABLE 3-27

BENEFITS OF ONE MILE VISIBILITY IMPROVEMENT
IN THE EASTERN U.S. 1990 (1983 dollars)

	Benefits per household	Total Benefits ($000)
Alabama	167	233666
Connecticut	144	182760
Delaware	141	34578
District of Columbia	209	60670
Florida	116	514983
Georgia	179	380602
Illinois	206	902688
Indiana	220	464536
Kentucky	199	269036
Maine	117	51153
Maryland	230	413287
Massachusetts	149	339302
Michigan	194	706202
Mississippi	144	124967
New Hampshire	160	58592
New Jersey	157	465041
New York	163	1120832
North Carolina	171	390607
Ohio	201	848300
Pennsylvania	179	799842
Rhode Island	111	42780
South Carolina	193	220656
Tennessee	194	333294
Vermont	154	31456
Virginia	233	495 369
West Virginia	198	132774
Wisconsin	169	314799
TOTAL		9,932,774

Note: A detailed discussion of visibility scenarios is given in section 4.

Two conclusions are suggested by this comparison. The first is that improved traffic safety is one of the major benefits of visibility improvement--about 7% of the total. A plausible conjecture is that there are several such major areas of bnefit, plus a great number of areas where much smaller benefits are derived. One such example is the benefit to spectators of major league baseball in the entire U.S.--somewhat less than $1 million annually resulting from the hypothetical one mile improvement, or less than one ten-thousandth of the total. This is not a big part of the overall picture, but it undoubtedly has importance to some people. (See section 3.2.3.)

The second and more important conclusion is that the secondary-data and willingness-to-pay results appear to be consistent. While we cannot be certain that a far more exhaustive secondary-data study would confirm the survey results by adding up to the same total, nevertheless these results are plausibly related to each other. Thus the evidence from the two approaches gives reason to have confidence in both as a means of valuing this elusive non-market good.

Section 3 contains controlled experiments that directly compared secondary-data and contingent valuation results in well defined situations. These results corroborate our conclusions about the one mile improvement experiments. In section 3.4, a contingent market in visibility for view-oriented residences among high-rise residents along Lake Michigan in Chicago was established. A hedonic demand analysis was carried out for the same group of subjects. The similarity of results confirmed the reliability of each approach for policy analysis. A similar study of demand-based and contingent valuation in section 3.3.2 of Hancock Tower visitation rejected the hypothesis that different results are obtained from the two analytic approaches.

In future work, the findings of significant effects of visibility on the other activities that have been considered in this section (section 3)--namely, air traffic and recreation in addition to baseball attendance--could be used to develop benefit estimates to compare with the contingent valuation estimates.

SECTION 4

Use of Results to Estimate Benefits for the Eastern United States

4.1 EVALUATION OF POLICY EFFECTS ON VISUAL RANGE

This chapter provides a detailed illustration of the application of the visibility value function developed in Section 2 to analysis of policy benefits. The visibility value function indicates how people's expressed willingness to pay to enjoy visibility improvements or to prevent visibility deterioration depends on their personal characteristics and on prevailing visibility conditions where they live. This function is general in that it can be used to estimate visibiltiy benefits associated with any amount of pollution reduction. The benfits are obtained by summing over affected areas taking account of willingness to pay for the change in visibility that will be brought about in each area by the pollution policy.

Forecasting visibility policy effects requires comparing a without-policy or base-case scenario with one or more scenarios of regulatory stringency. In this chapter, the visibility value function is applied to four policy hypothetical or illustrative policy scenario for electric and utility pollution control relative to a base-case scenario. Benefits connected with these illustrative scenarios are estimated for the year 1990. Specifically, per-household and aggregate benefits are estimated for each eastern state and the eastern United States.

A method is needed which relates reductions in pollution emissions from the scenarios to visibility improvements. In the present chapter, the relation between emissions and visibility is provided by results from research at Argonne National Laboratory. The major task of the chapter is to estimate visibility benefits using the visibility value function.

4.2 ILLUSTRATION OF METHOD

4.2.1 Outline and Summary

Step A in the analysis of visibility regulation was to establish policy alternatives. Alternative policies produce different patterns of visibility improvements whose effects need to be evaluated in order to make a policy choice. Four such policies were considered. In addition to the policy scenarios a without-policy or base-case scenario was formulated. The base-case scenario is a judgement as to the most likely regulatory climate in the absence of a visibility policy. It provides the standard against which the benefits of the policy scenarios are measured.

Step B was to forecast emissions under the base-case and hypothetical-policy scenarios by type of emitter, season and amount of pollution. These forecasts depended in part on the technical requirements of pollution abatement. To an even greater extent the emissions forecasts depended upon forecasts of future levels of economic activity.

Step C was to forecast the spatial distribution of ambient air quality. The relationship between emissions and ambient air quality depends upon the way emissions are dispersed geographically and the chemical transformations that occur during dispersion. This step was performed for each of the scenarios by means of the Argonne long-range-transport model. [Rote, 1982]
Step D was to measure the effects of ambient air quality on visibility resulting from each hypothetical scenario. The solution to this problem, also supplied by Argonne [Rote, 1982b], provides a set of predictions as to the course of visual air quality on a state by state basis in the future.

Step E was to use the visibility value function to establish values associated with alternative pollution control strategies. Each hypothetical scenario produced a set of improvements in visual range for each state in future years. The function estimated the value of these improvements to a state as the sum of the value of the local component and value of improvements in other parts of the region due to existence and option values. Non-local improvements are less valuable to the state depending upon their distance from the state. The value of visibility improvements is the sum of all local and non-local improvements for all states in a given year. The visibility value function is used to evaluate improvements for each state in 1990 for each of the four hypothetical policy scenarios.

4.2.2 Step A: Establish Hypothetical Policy Scenarios and Estimate Visibility Effects

In this step, a base case and four illustrative policy scenarios are considered. [Rote, 1982b] The base case the three hypothetical policies that yield improvements are summarized in Ta.4-1. They are as follows:

4.2.2.1 Base Case: Scenario 2

This scenario assumes that all electric utilities governed by State Implementation Plans (SIP) meet promulgated regulations by 1985. Compliance is determined by comparing annual emissions with specified SIP regulations.

For industrial emitters that burn coal, the base-case scenario assumes that large units burn low sulfur coal, and medium and small units comply with SIP regulations. For oil-fired industrial emitters, the base case assumes that large units burn medium- or low-sulfur coal, and small units comply with SIP regulations. These industrial assumptions are maintained for all of the scenarios. All other emitters are assumed to continue emitting at the 1979 rate in the base-case scenario. This assumption about other emitters is also used in each of the other scenarios.

This scenario is crucial to policy analysis because it measures without-policy or base-case conditions against which policy effects are measured. It provides the basis for an estimate of future pollution by type of emitter in the absence of the policy being evaluated.

4.2.2.2 Hypothetical Control Scenarios

The state of completion of the Argonne study necessitated limiting the analysis to illustrative policies in which utilities are controlled more stringently than in the base case, but emissions for other sources remain as in the base case. No implication is intended that this combination of controls would be chosen.

The scenarios are numbered according to increasing stringency of control. Remembering that Scenario 2 is the base case, and shows some improvement over 1979, the control scenarios are as follows:

TABLE 4-1

<u>Scenario 1 (1979 status quo).</u>

All utility units continue to emit SO_2 at the 1979 rate. Units with operating scrubbers keep them; units with planned scrubbers install them.

<u>Scenario 3 (First level of increased stringency for utilities).</u>

All unility units covered by SIP regulations are required to meet promulgated regulations by 1985. No such unit is allowed to exceed 4 pounds SO_2 emissions per millions BTU's from fuel used to produce electricity.

<u>Scenario 4 (Second level of increased stringency for utilities).</u>

All utility units covered by SIP regulations are required to meet promulgated regulations by 1985. No such unit is allowed to exceed 2 pounds SO_2 emissions per million BTU's from fuel used to produce electricity.

<u>Scenario 5 (Third level of increased stringency for utilities).</u>

All utility units covered by SIP regulations are required to achieve a 50 Percent reduction in SO_2 emissions beyond SIP compliance levels by flue gas desulfurization retrofitting where retrofitting is most cost effective.

4.2.3 Step B: Forecast Emissions Under the Hypothetical Policy Scenarios

Sulfur dioxide is the emitted pollutant of central importance to the analysis because it is a precursor of ambient air constituents that cause the greatest extinction of visual range. Argonne obtained the scenarios underlying forecasts of future emissions from electric utilities from Technekron, Inc., and those underlying the industrial emissions forecasts from ICF, Inc.

Emissions estimates are made for the base-case and the four hypothetical-policy scenarios to the year 2000. The model requires that the conditions under which emissions take place be specified in detail. These conditions include type of emitter (utility, industrial, other), stack height (short, medium, tall), season (summer, winter), and fuel type (coal and oil of various grades). The symbol specifying the amount of emissions from a type under a given control scenario is $Q^{(m)}_{jkt}$, where

Q is emissions of SO_2 in kilotons per year;
m is the scenario (m = 1, ..., 5 as described under Step A;
j is the state from which emissions originate. All emissions are aggregated and assumed to originate from the geographic center of the state;
k stands for the other conditions under which emissions occur: type of emitter, stack height, season, fuel type. k = 1, ..., n for each of these conditions;
t is the year. t = 1980, ..., 2000. Hereafter, t will be understood to be present but not written down.

4.2.4 Step C: Forecast Spatial Distribution of Ambient Air Quality

Forecasting pollution is a regional problem because there are many source regions, defined as states, and many receptor states. Each state is both a source and a receptor, and the source-receptor relationship is a complicated one. The Argonne long-range-transport model accounts for the processes by which pollutant emissions are transported and transformed into ambient pollution within a regional framework [Rote, 1982a]. All of the states in the present project study area are represented (eastern United States).

Based upon the pollution emissions variable, $Q_{jk}^{(m)}$, an equation can be written down which expresses the key relationships of the ambient air forecast:

(4-1) $$X_i^{(m)} = t_i \sum^{j} \left\{ e_{ij} \sum^{k} Q_{jk}^{(m)} \right\} ,$$ where

$X_i^{(m)}$ is ambient pollution in state i under scenario m, measured in $\mu g/m^3$ of SO_4;

e_{ij} is the amount of emissions from state j reaching state i, per kiloton of emissions in state j;

t_i is the amount of ambient pollution in state i resulting from a kiloton of emissions of SO_2 arriving in the state.

Eq.(4-1) may be explained as follows. To solve for $X_i^{(m)}$, first sum emissions $Q_{jk}^{(m)}$, over the k source types in state j, where $Q_{jk}^{(m)}$ is obtained from Step A. Multiply the resulting $\sum^{k} Q_{jk}^{(m)}$ emissions by e_{ij} to obtain emissions from state j arriving in state i. Sum over all states j to obtain total emissions arriving in state i, and multiply by t, to obtain the state's ambient pollution.

In the Argonne model, air-quality variables estimated on a state-by-state basis are as follows:

Model-predicted sulfate ion concentrations;

Estimated sulfate ion concentrations computed by adjusting the model-predicted values with regression parameters;

Fine particle (FP) concentrations computed from sulfate ion concentrations estimated with regression equations;

FP concentrations computed from an alternative theoretical/empirical relationship between FP mass and other constituents;

Controllable sulfate mass concentrations computed from a theoretical relationship between sulfate ions and other FP constituents;

Estimated first and second 24-hour maximum FP mass concentrations;

Model-predicted sulfate ion wet and dry deposition rates [Rote, 1982a].

Several qualifications are noted in the Argonne report which affect the applicability of the results discussed in this chapter. First, emissions from each source state are assumed to emanate from a single point at the geographic center of the state. Second, modeling results need more comparisons with actual visibility measurements. Available comparisons show a good correspondence; however, adjustments have been made to model-generated visibility endowments in estimating benefits in the Report. Third, the Argonne Report questions the validity of the base-case industrial scenario as representative of likely economic trends between 1980 and the year 2000.

4.2.5 Step D: Estimate Visibility Effects of Scenarios

Predictions of visibility levels for 1990 for the base case and policy scenarios are given in Ta.4-2 for each state considered in this study. Estimates of actual visibility in 1980 are also given.

The analysis of visibility effects may be represented by the following equation, representing the approach used in the Argonne study:

$$\Delta V_i^{(m)} = f\left\{\left[X_i^{(m)} - X_i^{(0)}\right], Y_1, Y_2, \ldots\right\}, \tag{4-2}$$ where

$\Delta V_i^{(m)}$ is the improvement in visual range in miles in the i^{th} state caused by policy scenario m. It is computed from a theoretical-empirical relationship involving sulfate ion concentration and other factors in Y_i, defined below;

TABLE 4-2

Visibility Projections in Miles
for Base Case and Three Control Scenarios, 1990

STATE	Actual Visibility 1980	Base Case Scenario 2: SIP Compliance by 1985	Scenario 3: SIP SO_2 Emission Limits 41bs. per million BTU	Scenario 4: SIP SO_2 Emission Limits 21bs. per million BTU	Scenario 5: SO_2 Emissions 50% below SIP Compliance Levels
Alabama	14.3	13.7	13.7	14.3	14.3
Connecticut	9.9	9.9	9.9	10.6	11.2
Delaware	10.6	9.9	10.6	11.2	11.8
D.C.	10.6	10.6	10.6	11.8	12.4
Florida	14.9	14.3	14.3	14.9	14.9
Georgia	13.7	13.0	13.0	14.3	14.3
Illinois	13.0	13.0	13.0	14.3	14.3
Indiana	9.9	10.6	11.2	11.8	13.0
Kentucky	10.6	11.8	11.8	13.0	13.7
Maine	13.7	13.7	13.7	14.3	14.3
Maryland	10.6	9.9	10.6	11.2	11.8
Massachusetts	10.6	9.9	9.9	10.6	11.2
Michigan	13.0	13.0	13.0	13.7	14.3
Mississippi	15.5	14.3	14.3	14.9	14.0
New Hampshire	11.8	11.8	11.8	13.0	13.0
New Jersey	10.6	9.9	10.6	11.2	11.8
New York	10.6	10.6	11.2	11.8	13.0
North Carolina	13.0	12.4	13.0	13.0	13.7
Ohio	8.7	9.3	9.9	11.2	12.4
Pennsylvania	8.7	8.7	9.3	9.9	11.3
Rhode Island	10.6	9.9	9.9	10.6	11.2
South Carolina	13.7	13.0	13.0	13.7	13.7
Tennessee	11.8	11.8	11.8	13.0	13.7
Vermont	11.8	11.8	11.8	12.4	13.0
Virginia	10.6	10.6	11.2	11.8	12.4
West Virginia	9.9	9.9	10.6	11.2	12.4
Wisconsin	14.9	14.3	14.9	14.9	15.5

$X_i^{(m)}$ is ambient pollution as defined and calculated in Step C, equation (1) ; $X_i^{(m)}$ is ambient pollution in state i under scenario m; $x_i^{(0)}$ is base case ambient pollution in state i;

Y_i are variables such as humidity and fine particle constituents other than sulfate ion which affect the relationship between ambient air quality and visual range;

Eq. (4-2) is a summary of a study of the determinants of visual range in the eastern United States by D. M. Rote. [Rote, 1982a]

4.2.6 Step E: Estimate the Value of Visibility Benefits of Hypothetical Pollution Control Strategies

In this step the visibility value function is applied to the visibility effects obtained in Step D. Visibility improvement attributable to a policy equals the difference between visibility under a policy scenario and base-case visibility. The value of visibility improvement depends upon the size of the improvement, the characteristics of the people enjoying it, and the prevailing level of visibility. The value of an extra mile of visual range depends upon the income of a household, for example, and the number and ages of household members. An extra mile of visibility is valued more when prevailing visibility is low than when it is high.

The relationship between the expressed valuations and the influential factors, or predictor variables, was specified according to economic theory and measured econometrically in Section 2 of this study. The resulting relationship is the visibility value function. By using the visibility improvements and the predictor variables, a predicted value for visibility improvement was calculated for each state in the eastern United States.

In symbols, the use of the visibility value function in benefit estimation can be expressed as follows:

$$(4\text{-}3) \quad B^{(m)} = \sum^{j}[1 - \exp(-\gamma \Delta VS_{jm})](\alpha + \sum^{i}\beta_i X_{ij})N_j \quad , \text{ where}$$

$B^{(m)}$ is aggregate dollar benefits of scenario m over the base case;

ΔVS_j is change in visibility services from the m^{th} scenario over the base case in the j^{th} state as calculated using eq. (2-43) in Section 2.4;

X_{ij} is the value of the i^{th} household characteristic in the j^{th} state;

N_j is the number of households in the j^{th} state; and

the parameters γ , α and the β_i's are as given in Ta.2-20 of Section 2.4.

Regarding the values of the household characteristics (X_{ij}'s), for the following variables, samplewide means were used: respondent believed he had an excellent view (EXVIEW), female head of household (FEMHOH), equipment index (EQUIP), bad eyesight (POOREYES), rural residence (RURAL), activity index (ACT), ownership of other residential property in eastern U.S. (PROP), and ownership of occupied unit (OWN). For other variables, state-specific values were used. These are household income (INCOME), income squared (INCOME2), age of household head (HOHAGE), education of household head (HOHED), household size (HSLDSIZ), visibility endowment (VISENDOW), percent nonwhite (NONWHITE), dummies for Atlanta (A), Cincinatti (C), Miami (M), and Washington, DC (W).

In summary, the preceeding steps summarize the entire analytic framework underlying the estimates of benefits that begins with the statement of policy alternatives and ends with a dollar estimate of the benefits of these policies. While the policy scenarios examined here are illustrative, the established framework has been shown to be entirely general and capable of analyzing any set of policy alternatives that are of regulatory interest.

The following sections explain in more detail how the visibility value function is applied, and present benefits estimates for hypothetical policy scenarios for the year 1990.

4.3 BENEFITS OF HYPOTHETICAL POLICY SCENARIOS.

In this section, calculations for two states are described to explain how the visibility value function is used to derive benefits estimates. The calculations illustrate the spatial nature of regional visibility effects. Benefits for each state and for the eastern United States as a whole for the hypothetical policy scenarios are presented.

4.3.1 Measurement of Physical Effects and Willingness to Pay for Improvements

4.3.1.1 Forecast Emissions under Scenario 5 in Georgia and Ohio (Step B)

Using Argonne scenario simulations, this section illustrates the policy analysis process described in Section 4.2. For illustrative purposes we consider two eastern states, Ohio and Georgia, and trace through the effects of scenario 5 implementation in terms of the five steps previously outlined. Ta.4-3, base-case emissions in the two states are given by the row "SO_2 emissions" in kilotonnes per year. In the absence of visibility policy, ambient SO_2 emissions in Georgia would increase from 630 kilotonnes in 1980 to 873 kilotonnes in 1990 and 1026 kilotonnes in 2000.

Under scenario 3, on the other hand, Georgia's SO_2 emissions would be 554 kilotonnes in 1990 instead of 873, and 567 kilotonnes instead of 1026 in 2000. Thus scenario 3 produces a 36 percent reduction in emissions in Georgia during the 1980's and a 15 percent reduction during the 1990's compared with the base case projection. In Ohio the emissions pattern is quite different. Ohio's 1980 emissions are about four times higher than Georgia's--2748 kilotonnes vs 630 kilotonnes. However, Ohio's emissions are forecasted to decline between 1980 and 2000, even under the base-case forecast. Furthermore, policy effects in Ohio are even greater than in Georgia. In Ohio, scenario 3 produces a 58

TABLE 4-3

Policy Effects in Two States[1]

GEORGIA

	Base Case: Scenario 2			Policy Scenario 5		Policy Effects[4]			
						Amount	%	Amount	%
	1980	1990	2000	1990	2000	1990		2000	
SO_2 emissions[1]	630.0	873.0	1026.0	554.0	567.0	-319.0	-36.0	-459.0	-45.0
Ambient SO_2[2]	7.3	9.8	11.7	7.1	8.2	- 2.7	-28.0	- 3.5	-30.0
Visibility[3]	13.7	13.0	13.0	14.3	13.7	1.3	10.0	.7	5.4
Aggregate benefits (per household)[5]						365 (168)			

OHIO

	Base Case: Scenario 2			Policy Scenario 5		Policy Effects			
						Amount	%	Amount	%
	1980	1990	2000	1990	2000	1990		2000	
SO_2 emissions	2748.0	2300.0	2207.0	964.0	1056.0	-1336.0.	-58.0	-115.0	-52.0
Ambient SO_2	37.0	32.8	32.8	17.8	19.8	- 15.0	-46.0	- 13.0	-40.0
Visibility	8.7	9.3	9.3	12.4	11.8	3.1	33.0	2.4	27.0
Aggregate benefits (per household)						1516 (360)			

[1] Kilotonnes per year

[2] Micrograms per cubic meter

[3] Miles

[4] Physical effects are drawn from simulations provided by D.M. Rote of Argonne [Rote, 1982a, 1982b]

[5] Aggregate benefits in millions of dollars per year; household benefits in (dollars per year). From Ta.4-6.

percent emissions reduction during the 1980's. and a 52 percent reduction during the 1990's. The combined effect of trends and policy effects in the two states therefore, is that Ohio emissions in 1980 are over four times greater than Georgia emissions, whereas by 2000 Ohio emissions are less than twice as large as Georgia's.

4.3.2.1 Forecast Ambient Air Quality under Scenario 5 in Georgia and Ohio (Step C)

Ambient air quality is given by the row "Ambient SO_2" in micrograms per cubic meter ($\mu g/m^3$) in Ta.4-3. In 1980, ambient air quality is over five times worse in Ohio than in Georgia by the SO_2 criterion--37.0 $\mu g/m^3$ in Ohio vs 7.3 $\mu g/m^3$ in Georgia. As in the case of emissions, air quality in Ohio is projected to improve in the base case (from 37.0 $\mu g/m^3$ in 1980 to 32.8 $\mu g/m^3$ in 2000) and to deteriorate in Georgia (from 7.3 $\mu g/m^3$ in 1980 to 11.7 $\mu g/m^3$ in 2000). As for the policy effects of scenario 5 in the two states, both states experience improvements in 1990 and 2000, compared with the without-policy or base-case scenario. However, taking account of both trends and policy effects in the two states, Georgia experiences a net deterioration in ambient air quality by 2000 (from 7.3 $\mu g/m^3$ to 8.2 $\mu g/m^3$), while Ohio experiences a net improvement by 2000 (from 37.0 $\mu g/m^3$ to 19.8 $\mu g/m^3$).

4.3.1.3 Forecast Visibility Effects of Scenario 5 in Georgia and Ohio (Step D)

Visibility effects of scenario 5 are given by the row labeled "Visibility" for each state. In the absence of a visibility policy, Georgia is forecasted to experience a reduction in visibility--from 13.7 miles in 1980 to 13.0 miles in 2000. Ohio visibility improves from 8.7 to 9.3 miles over the same period in the base forecast. The effect of scenario 5 is to convert deteriorating visibility in Georgia into improved visibility in 1990 (14.3 miles vs 13.0 miles). By 2000, visibility under scenario 5 has fallen back to its 1980 level of 13.7 miles, but it is still better than it would have been in the absence of the policy--13.0 miles. The policy gains in Georgia are 1.3 miles during the 1980's and 0.7 miles in the 1990's. In Ohio, visibility would have improved even in the absence of a visibility policy--from 8.7 miles in 1980 to 9.3 miles in 1990 and 2000. But the policy effect is to produce an even greater improvement--to 12.4 miles in 1990 and 11.8 miles in 2000. The policy gains in Ohio are 3.1 miles in the 1980's and 2.4 miles in the 1990's.

4.3.1.4 Forecast Willingness to Pay for Visibility Improvements from Scenario 5 in Georgia and Ohio (Step E)

Monetary values of visibility improvements for each state are derived by substituting appropriate values for each variable into the visibility value function. The result is an estimate of the state population's maximum willingness to pay for improved visibility in a given year. For example, from Ta.2-20, Section 2.4.5, the contribution of changes in visual range to the estimate of Ohio's willingness to pay for the policy improvement is equal to 155.844 times (5.14 minus 4.57)(times 1.229)--the parameter estimate of VISENDOW times Ohio's 1990 visibility index change under scenario 5 times 8. The sum of similar calculations over all the function variables in eq. (2-43), Section 2.4.4 equals Ohio's policy benefit.

Total benefits are estimated to be about $1.5 billion in Ohio and $350 million in Georgia in 1990 under scenario 5. On a per-household basis, Ohio benefits are about $360 and Georgia benefits about $170. These values correspond to a 3.1 mile visibility-policy improvement in Ohio and a 1.3 mile visibility-policy improvement in Georgia.

Ohio derives larger policy benefits than Georgia for a variety of reasons. First, Ohio's population is larger. While household benefits in Ohio are about 1.5 times greater than in Georgia, aggregate Ohio benefits are over four times greater than aggregate Georgia benefits. Second, the policy effect is almost two miles greater in Ohio than in Georgia, largely because of the much greater emissions reduction required by Ohio. By dividing the percentage change in visibility by the percentage change in emissions, we obtain a number that measures the relationship between local benefit and local clean-up effort. This may be done using numbers in Ta.4-3 for each state in 1990 and 2000. The result is that the ratio is one fourth to one half as large in Ohio as in Georgia. One of the main reasons for this result is that local visual range is affected by distant sources of pollution as well as local sources. Hence under scenario 5, Ohio derives visibility benefits from out-of-state emissions reductions to a greater extent than Georgia.

The third reason is that Ohio citizens derive greater benefits from visibility improvements in other states than do people living in Georgia. This is because Ohio is more centrally located than Georgia with respect to regional visibility improvements. According to the visibility value function, visibility improvements in other eastern states are worth more to the citizens of Ohio than they are to the citizens of Georgia.

4.3.2 Aggregation of Physical Effects in the Eastern United States (Step C)

Ta.4-2 summarized the results of each of the alternative policies in miles of local visibility by state. Comparison of scenarios 3, 4, and 5 with the base case demonstrates the rather complex geographic distribution of local visibility improvements that results from alternative policy standards.

Effects of policy on local visibility, as recorded in Ta. 4-2, do not however describe the entire policy effect of relevance to the local area. As explained in Part 2, distant visibility conditions are part of local endowment. In other words, the entire column of improvements associated with each regulatory strategy is relevant to the measurement of benefits in each state, because they are all part of each state's visibility endowment.

Ta.4-4 gives measures of visibility sources for each state. The measure of visibility services is a weighted contribution of visibility in all states to the state in question, as obtained from eq.2-43 in Section 2.4. Ta.4-4 was derived by using projected policy improvements for all states to calculate visibility services for each state. Ta.4-5 gives an idea of the relationship between the visibility services measure and local visibility in miles for each state. States are ordered from highest to lowest on the endowment index for 1980. The corresponding visibility in miles in each state does not follow the same order. Florida, for example, has relatively high local visibility, yet ranks last on the index scale because of its geographic remoteness from the rest of the coutry. Visibility in other areas contributes relatively little to Florida's endowment. Fig.4-1 illustrates the visibility endowment index for 1980.

4.3.3 Aggregation of Scenario Benefits in the Eastern United States, 1990--Preliminary Estimates Subject to Revision

Ta.4-6 presents 1990 policy benefits for the three improvement scenarios. Total program benefits for the three illustrative scenarios in the year 1990

TABLE 4-4

Measure of Visibility Services (VS)

STATE	Base Case 1980	Base Case 1990	Policy Scenarios, 1990: 3	4	5
Alabama	4.59	4.52	4.53	4.67	4.72
Connecticut	3.72	3.70	3.75	3.90	4.06
D.C.	4.66	4.59	4.74	4.94	5.16
Delaware	3.73	3.67	3.78	3.92	4.08
Florida	3.51	3.44	3.46	3.56	3.58
Georgia	4.34	4.26	4.28	4.47	4.52
Illinois	5.52	5.52	5.56	5.73	5.81
Indiana	5.12	5.19	5.28	5.46	5.66
Kentucky	5.01	5.11	5.16	5.40	5.55
Maine	4.93	4.92	4.94	5.13	5.18
Maryland	4.71	4.63	4.80	5.00	5.24
Massachusetts	4.20	4.12	4.17	4.36	4.53
Michigan	4.94	4.94	4.98	5.12	5.26
Mississippi	4.94	4.83	4.84	4.95	4.99
New Hampshire	5.02	5.00	5.04	5.34	5.46
New Jersey	3.91	3.84	3.96	4.11	4.29
New York	4.36	4.34	4.48	4.65	4.93
North Carolina	4.53	4.44	4.56	4.66	4.80
Ohio	4.51	4.57	4.68	4.91	5.14
Pennsylvania	4.51	4.50	4.66	4.85	5.15
Rhode Island	3.70	3.64	3.68	3.84	3.98
South Carolina	4.54	4.46	4.52	4.67	4.76
Tennessee	5.11	5.11	5.14	5.37	5.49
Vermont	4.90	4.89	4.94	5.17	5.35
Virginia	4.87	4.84	4.99	5.17	5.37
West Virginia	4.69	4.69	4.82	5.01	5.25
Wisconsin	5.58	5.51	5.59	5.64	5.75

Source: Explained in text.

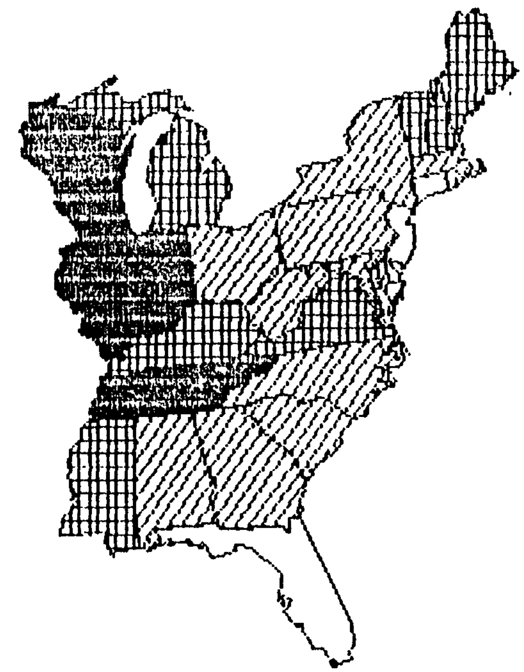
TABLE 4-5

Ranking of States by 1980 Visibility Endowment

State	Visibility Endowment Index	Visibility in Miles
Wisconsin	5.58	14.9
Illinois	5.52	13.0
Indiana	5.12	9.9
Tennessee	5.11	11.8
New Hamsphire	5.02	11.8
Kentucky	5.01	10.6
Mississippi	4.94	15.5
Michigan	4.94	13.0
Maine	4.93	13.7
Vermont	4.90	11.8
Virginia	4.87	10.6
Maryland	4.71	10.6
West Virgina	4.69	9.9
District of Columbia	4.66	10.6
Alabama	4.59	14.3
South Carolina	4.54	13.7
North Carolina	4.53	13.0
Ohio	4.51	8.7
Pennsylvania	4.51	8.7
New York	4.36	10.6
Georgia	4.34	13.7
Massachusetts	4.20	10.6
New Jersey	3.91	10.6
Delaware	3.73	10.6
Connecticut	3.72	9.9
Rhode Island	3.70	10.6
Florida	3.51	14.9

FIGURE 4-1

VISIBILITY ENDOWMENT BY STATE, 1980



LEGEND: VISENDOW 4 4.5 5 5.5

VISENDOW IS THE STATES 1980 VISIBILITY INDEX NUMBER

TABLE 4-6

Annual Household Benefits and Total State Benefits
Relative to Base Case, 1990

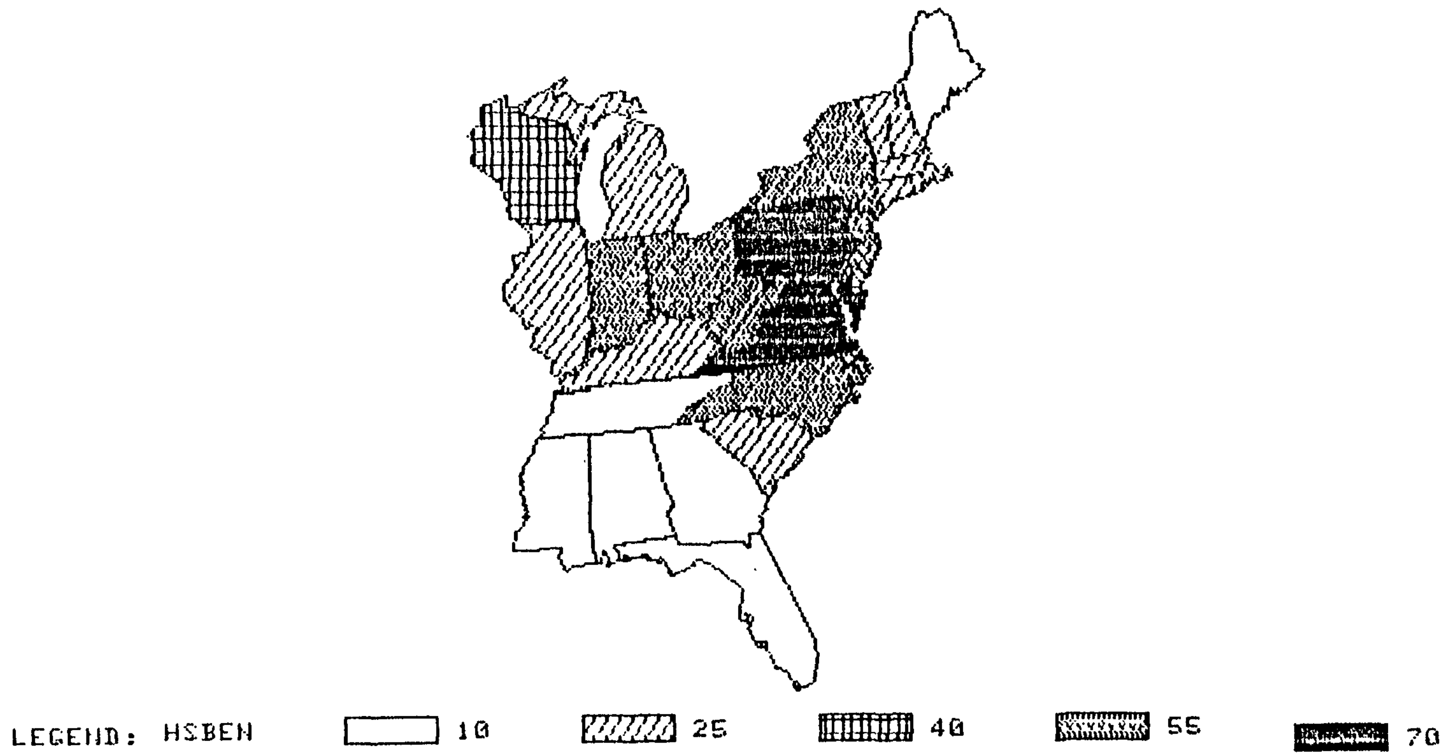
	Scenario 3		Scenario 4		Scenario 5	
	State Benefits ($ millions)	Benefits per Household ($)	State Benefits ($ millions)	Benefits per Household ($)	State Benefits ($ millions)	Benefits per Household ($)
New York	397	58	1111	162	2394	350
Pennsylvania	315	71	820	184	1725	386
Ohio	224	53	773	184	1516	360
Virginia	163	77	418	197	785	370
New Jersey	152	52	430	146	862	292
Maryland	150	84	388	216	756	421
North Carolina	111	49	244	107	492	216
Indiana	107	51	359	171	714	339
Illinois	93	21	634	145	1029	236
Wisconsin	89	48	174	93	368	198
Michigan	78	21	421	116	904	249
Massachusetts	48	21	282	124	588	260
West Virginia	39	59	109	163	219	328
Kentucky	30	22	211	157	380	282
South Carolina	30	26	126	110	217	190
Connecticut	28	22	211	157	380	282
Tennessee	24	14	244	142	427	249
Georgia	22	10	230	109	355	168
D.C.	20	70	56	192	107	371
Florida	20	4	214	48	342	77
Alabama	11	8	110	79	176	126
Delaware	11	44	30	123	61	248
New Hampshire	8	21	72	197	114	311
Mississippi	6	6	57	66	88	102
Rhode Island	6	14	33	87	72	187
Vermont	5	23	31	153	59	289
Maine	4	10	49	113	73	167
TOTAL	2,193		7,766		15,134	

range from about two billion dollars (scenario 3) to about fifteen billion dollars (scenario 5).

New York, Pennsylvania, Ohio, Illinois, Michigan, and New Jersey are the six leading beneficiaries of scenarios 4 and 5 in 1990. New York, Pennsylvania and Ohio lead in scenario 3 as well. These six states account for between 50 and 60 percent of eastern benefits under all three scenarios. New York, Pennsylvania and Ohio receive between 35 and 45 percent of eastern benefits under all three scenarios. The pattern of benefits is a little different on a per household basis. Still, it is the highly-populated and industrialized Northern states that place the highest value on improved visibility. While individual state rankings are somewhat sensitive to the specification of the endowment index and the aggregation pattern based upon contingent valuation, nevertheless the basic pattern is rather striking. Figure 4-2 illustrates the geographic distribution of benefits derived from scenario 3 relative to the base case.

FIGURE 4-2

Benefits per Household of Scenario 3
Relative to Base Case, 1990



4.4 SUMMARY OF PROJECT APPROACH TO VISIBILITY POLICY ANALYSIS

The monetary values of visibility policy benefits obtained in this chapter for alternative hypothetical policy scenarios illustrate the accomplishment of the major project objective, which was to develop a method of converting the physical effects on visual range of any proposed policy into values of benefits indicated by people's willingness to pay in the eastern United States. In this chapter we have described how policy scenarios that affect SO_2 emissions in the entire region can be translated into sets of effects on visual range in each eastern state. This phase of the work was completed by Argonne researchers, who simulated the visibility effects of several regional policy scenarios which control SO_2 emissions. The present chapter also describes how the resulting geographical changes in visual range are valued by the people of each state. This is accomplished by the visibility value function, which is the most improtant output of this study and is the expression that converts visibility changes into dollar values, based upon the personal characteristics of the resident population, and the goegraphic distribution and size of changes in visual range. Further work could include a more refined investigation of the effect of distance on valuation of visibility improvement. Additional econometric work could investigate estimations in view of truncation of the dependent variable. This work would extend the work reported on in Section 2.3. The importance of unique eastern views to willingness to pay for eastern visibility improvements could be studied in further contingent valuation survey work. These CV results would extend the analysis of the six-city survey in this report, which did not focus on existence of particular unique or spectacular scenic eastern views. The secondary-data analysis of section 3 could be refined and additional work on attaching monetary values performed. The further unique-view and secondary-data analysis could make possible a corroberation and refinement of the six-city survey results that would be more extensive than the one presently reported in Section 3.6 of this report. Further work along the lines discussed in this paragraph is being undertaken in a follow-up study now under way.

In closing, it should be emphasized that estimates of the visibility valuation function are the best we have at this time, but are subject to considerable refinement and investigation of reliability. The aggregate benefits estimates have been presented only for purposes of illustrating aggregation methodology. Care should be exercised that the results not be used out of context. The policy scenarios are for various kinds of utility controls and are not to be taken as indicating that these policies are actually being contemplated or should be enacted. A major point in illustrating the aggregation method is to emphasize there is no one unique value of increased visibility, but rather the benefits of a program affecting visibility depends on how much visibility is improved in different places, and on the numbers and characteristics of people in the places affected. It would defeat a major purpose of this study if the numbers in this chapter were applied out of context to other programs. The use of the results of this study should be to estimate differential improvements in visibility that would be brought about by a program and then to use the visibility function to obtain benefits in different areas which would then be summed. The purpose of this study has been to develop operational tools. The tools can be applied for actual policy purposes, but they have not been so applied in this study.

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EXECUTIVE SUMMARY

Visibility is a pervasive and inescapable phenomenon, subject to both general and periodic deterioration, which affects extremely large numbers of people. The relative neglect of visibility as a subject of investigation appears to be due not to its lack of importance, but rather to the fact that it is more difficult to value than many other environmental attributes.

Previous work on visibility has concentrated on sparsely populated areas of the West. The present research, concerned with visibility in the eastern United States, deals with larger numbers of people under a wider variety of circumstances. People in urban and rural areas are affected in the course of daily living, and a variety of special activities centering on recreation and related activities are sensitive to visibility conditions.

Four major objectives have been accomplished by the research. The first objective was to use the contingent valuation (CV) approach to obtain information on values attached to visibility in the eastern United States. A major conceptual effort to extend and refine the CV technique preceeded data gathering. Several different CV formats were pre-tested in Chicago, followed by a six-city eastern survey.

The second objective was to define and estimate a visibility value function. The benefits of a visibility policy depend upon the extent of visibility improvement, on initial visibility conditions and their geographic distribution, and upon social and economic characteristics of people in various regions. Benefits are related to these variables in the visibility value function.

The third major objective was to identify particular activities likely to be influenced by visibility and to measure the effects of visibility on these activities using secondary data. Activities investigated were swimming.

television viewing, baseball attendance, Hancock Tower visitation, fatal and non-fatal traffic accidents, and air traffic counts. An important result of these studies is to corroborate findings from the aggregate function based on the contingent value (CV) approach.

The fourth major objective of project research was to establish a rigorous and operational method of aggregating visibility policy benefits over the entire eastern U.S.

OBJECTIVE ONE: CONTINGENT VALUATION SURVEY

The theory of household production was used in the development and use of a contingent valuation (CV) survey questionnaire. There are seven basic modules to the CV instrument.

Module 1: Area Context Module

The area over which visibility improvements were offered had to be clearly comprehended by each individual. For the research to provide results on regional differences in air quality improvement, it was important to collect willingness-to-pay (WTP) data for improvements in visibility (i) in the individual's home sub-region, and (ii) in the whole study region. A map card and a portfolio of photographs were used to convey the size and diversity of the region over which visiblity is valued.

Module 2: Visibility Module

The nature of alternative levels of visibility was communicated via color photographs. This required a set of scenes representative of the area over which visibility changes were to be valued. For each level of visibility a set of the same scenes, with only the visibility different, was used. Some factual verbal material was used to quantify the visual range represented in each photo set. Separate photo sets were used to represent the sub-region, the entire East, and the West.

Module 3: Activity Module

To employ the household production model, it was necessary to know the following:

- the activities produced in the household,
- the inputs, other than visibility, used in activity production,
- the activity production technology used, and
- whether visual air quality is the only air quality input used and, if not, whether visual air quality is used by the subject as an indicator of other aspects of air quality. For example, the individual may avoid strenuous outdoor sports on days of poor visibility, not because visibility *per se* is an important input, but because he treats poor visual air-quality as an indicator of high pollutant concentrations which threaten respiratory stress.

The module served to sensitize the individual to the variety of activities in which he might value visibility.

Module 4: The Market Module

Contingent valuation established a hypothetical market and encouraged individuals to reveal their WTP by using that market. Major elements of this module described what was being purchased through the bid and the market rules regulating payment for and receipt of the good in question. To describe the good available for purchase, the general level of visibility as well as possible increments and decrements in visibility were portrayed in both photographs and narratives. Market rules provided assurance that the increment in visibility would be delivered if and only if the respondent was willing to pay.

Module 5: The WTP Data Collection Module

This module presented the fundamental WTP questions. Respondents bid first on local improvement, and then were asked how much they would add to their local bid to extend the improvement to the East and then to the entire U.S.

Module 6: Post-Bid Probing

With certain market rules and WTP formats, some individuals recorded a zero WTP which, in further questioning, turned out to be a protest against some aspect of the format rather than an accurate reflection of the value of the good offered. Probing of zero WTP's was an important element of the data-collection schedule.

Module 7: Socio-Demographic Data

This module collected an array of socio-demographic data, including full income concepts relevant to the processes through which individuals demand and hence value, visibility.

OBJECTIVE TWO: VISIBILITY VALUE FUNCTION

The objective of the contingent valuation research was to define and estimate a visibility value function. The theory of household production, fundamental to the development of the CV questionnaire, was equally important to the development of the visibility value function. The importance of regional or spatial economics was recognized and receives its most complete formulation in the visibility value function.

Central to the development of the visibility value function is the concept of visibility services. Visibility services are aggregates of visibility in different places, weighting each place's contribution by its distance, scenary, and quality. Accordingly, there is a production function relating visual services to these variables. Specifically the production function for visual services (VS) is

$$(1) \qquad VS_j = \sum_i VR_i^{\alpha_1} SM_i^{\alpha_2} D_{ij}^{\alpha_3} SC_i^{\alpha_4} \quad ,$$

where VS_j is household j's consumption of VS , VR_i is visual range in state i , SM_i is the area of state i in square miles, D_{ij} is the distance between household j and the center of state i , and SC_i is a measure of scenery in state i .

It was reasoned that the marginal benefit curve, or bid curve for a change in visibility services, should have the following properties:

Property 1: $BID(0) = 0$
Property 2: $BID'(\Delta VS) \geq 0$
Property 3: $BID''(\Delta VS) \leq 0$
Property 4: $\text{Limit } BID'(\Delta VS) = 0$ as $\Delta VS \rightarrow \infty$

A functional form was required that would be consistent with Properties 1 - 4 and capable of handling both continuous and discrete explanatory variables. Furthermore a functional form was needed which allows the bid curve to pivot around the origin with changes in the vector of explanatory variables while preserving these properties. The following negative exponential function was found to fulfill their requirements:

$$(2) \qquad BID = [1 - \exp(-\gamma \Delta VS)] \quad ,$$

which is monotonic increasing, passes through the origin, and has an upper limit of +1 for all positive values of γ . This gives the prototype bid function. A rotational vector of household characteristics H , is included:

$$(3) \qquad H = (\alpha + \Sigma\beta_i Z_{ij} + u_j) \quad ,$$

so that H is a linear combination of household characteristics Z , and there is an unobserved household-specific rotational parameter u .

The empirical bid curve is given by the product of (2) and (3) or

$$(4) \qquad BID_j = [1 - \exp(-\gamma \Delta VS_j)][\alpha + \Sigma\beta_i Z_{ij} + u_j)] \quad ,$$

where VS is given by (5), below, BID_j is the willingness-to-pay of household j , ΔVS is given by changes in equation (1) due to the program; a is a common intercept term (of rotation, not level of bid); Z is the vector of household characteristics with parameters β ; and u_j is the household-specific rotation of the bid curve.

The formula used to calculate VS for the empirical analysis is

(5) $$VS_j = \sum^{i} VR_i * SM_i * D_i^{-1.5} ,$$

where the exponent on the distance variable was estimated by a maximum likelihood method jointly with the vector of household characteristics and the parameter γ .

The estimation results for the visibility function are shown in Table 1. Overall, between one-half and two-thirds of the variation of BID is accounted for by the explanatory variables. The positive effect of a change in visibility on BID is reflected in coefficient of 0.700 for GAMMA. The common constant term ALPHA added to the individual estimated effects of household characteristics in determining rotation of the bid curve, is negative.

The first variable in H, rotating the bid curve is VISENDOW, the initial level of VS as calculated in (5) above. This variables has a positive effect and captures the net result of a pure endowment effect from diminishing marginal utility, a sorting effect and a substitution effect.

A point estimate of the income elasticity of rotation is 0.539 is computed, holding all non-income variables at their means. The first-order effect of income (INCOME) on BID is positive, and the second-order effect (INCOME SQUARED) and the income-age interaction effect (INCAGE) are negative.

TABLE 1

Non-Linear Least Squares Summary Statistics
Dependent Variable Bid

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
REGRESSION	22	130303017.02030957	5922864.41001407
RESIDUAL	3122	140479409.60049038	44996.60781566
UNCORRECTED TOTAL	3144	270782426.62079995	
(CORRECTED TOTAL)	3143	233630610.10008546	

PARAMETER (VARIABLE)	ESTIMATE
GAMMA	0.700
ALPHA	-472.606
VISENDOW	155.757
INCOME	14.797
INCOME2	-0.029
INCAGE	-0.172
HSLDSIZ	5.327
HOHED	-2.011
HOHAGE	1.586
EQUIP	4.417
EXVIEW	-67.139
BADEYES	12.065
ACT	5.175
PROP	97.183
FEMHOH	50.684
OWN	-138.736
RURAL	-41.049
NONWHITE	-78.691
A	139.928
C	-187.137
M	112.550
W	-17.078

The negative interaction term confirms the hypothesis that the marginal propensity to consume visibility decreases with age.

Turning to the human capital variables, the estimate of the education parameter (HOHED) is negative, SO that more educated persons tend to bid less, holding the other variables constant.

The age variable HOHAGE must be considered jointly with the variable INCAGE. For very low income households, age actually increases WTP for VS, but at an income of about $9,000 per year the net effect becomes negative. Nonwhites (NONWHITE) bid significantly less than whites, while females (FEMHOH) bid more than males.

Poor eyesight (BADEYES) and ownership of specialized capital equipment (EQUIP) did not have a clear effect. As expected, participation in activities (ACT) has a positive influence on bids,. reflecting the non-rivalness of visibility within the household. There is a negative influence of view quality (EXVIEW) on bids, which could be the result of diminishing marginal utility combined with a fixed factor (view).

With regard to the property ownership variables, home ownership (OWN) had a negative impact and the ownership of other residential property (PROP) had a positive effect.

In addition to the urban/rural dummy variable a set of four city-specific dummy variables were used to help account for unexplained differences between cities. Only four were used since one of the six city degrees of freedom has already been used up by the variable VISENDOW and the intercept terms uses another. The four cities with dummies are Atlanta, Cincinnati, Miami, and Washington, with variables names A, C, M, and W respectively. Boston and Mobile remain as the base.

OBJECTIVE THREE: EFFECTS OF VISIBILITY ON BEHAVIOR

To complement the contingent valuation work and the visibility value function based on it, a series of studies of the effects of visibility on particular activities was carried out. Evidence that the CV and behavioral results are consistent strengthens confidence in the results as well as the methods that have been developed to obtain them.

Swimming

The swimming model assumes a linear relationship of the form

$$P = \alpha + \beta_1 V + \sum_{i=2}^{n} \beta_i X_i \quad ,$$

where P is daily pool attendance, V is visibility, and X_i are other factors which effect attendance. Visibility was found to have a significant effect on attendance. The effect differs between years and ranges between 1.24 and 3.73 persons per tenth-of-a-mile increase in visibility. A one mile increase in visibility increases attendance from three to five percent.

Television and Baseball

Similar analyses were performed on afternoon television viewing and on Chicago Cubs baseball attendance. The effect of a one mile increase in visibility on afternoon viewing is that 0.134% of 3 million households stop watching T.V., or about 4000 households. Weekend viewing is reduced by an additional 400 households. An increase in visibility of one mile increases Cubs gate attendance by approximately 125 people. The change in consumer's surplus associated with increase in visibility is at least 2.7 cents per person in attendance, or approximately $30,000 for a typical season's attendance The benefit of a one mile visibility improvement represents somewhat less than one million dollars per year for baseball attendance in the entire U.S.

Hancock Tower Recreation

The Chicago Hancock Tower offered an opportunity to determine the effects of visibility on the demand for view services. Using visitation data, it was possible to estimate the demand for Hancock Tower view services as a function of admission price, visibility, and a set of demand shifters. A mean per person consumer surplus of $2.12 in 1981 prices was computed from the demand estimate. Assuming that similar experiences are obtainable in other areas of the region, aggregate consumer surplus would be $275 million in 1981 prices.

Contingent valuation responses were also obtained at the Tower. The results indicate no significant difference between demand-based estimates and contingent valuation bids.

View-Oriented Residences

An analysis of view-oriented submarkets of the residential housing market was undertaken. The objectives were: (1) to measure the values of views and view characteristics including visibility using a survey instrument which establishes a contingent market for each; (2) to measure the values of views and view characteristics using a hedonic-demand analysis of housing consumption for the same group surveyed and (3) compare the contingent values from the survey and the implicit values from the housing market for individuals dwelling in view-oriented residences.

The similarity of the contingent and implicit values for height (10 floors up), the high response rate on the bidding experiment and the significant coefficients in the renters' housing hedonic equation suggested that contingent value and market values are similar.

Air Traffic

To investigate the effects of visibility on air traffic, empirical estimates were made of visibility effects on take-offs and landings at three Chicago-area airports. The effects of visibility on the air traffic counts were found to be positive and highly significant in all areas. The elasticities of traffic counts with respect to miles of visibility were 0.415, and 0.392 and 0.250 at Aurora, DuPage and Meigs Field airports respectively. The other variables in the regressions, including rainfall, snow, fog, temperature, wind speed, wind direction, and day of the week were in almost all cases of expected sign and significant.

Auto Traffic

A model of the relationship between travel cost, accident rates, weather conditions, improvement in visibility, vehicle speed, and traffic congestion was developed. It was shown that the total effect of an improvement in visibility on accident rates depends crucially on the effect of improvements in visibility on vehicle speed.

The empirical estimations of the relationship between improvements in visibility, weather variables and traffic casualties show that visibility improvements lead to significant reductions in non-fatal accidents in both Cook and DuPage Counties, in the Chicago SMSA. This result is consistent with the partial effect of improvements in visibility on highway casualities. While the occurrence of rain and/or snow leads to an increase in the number of non-fatal accidents in Cook and DuPage Counties, the results also show that an improvement in visibility in the presence of snow leads to a decrease in the number of non-fatal accidents in both counties.

Results of linear probability models in analyzing traffic fatalities show that an improvement in visibility during the weekends leads to an increase in the probability of occurrence of fatal accidents in Cook and DuPage Counties. Visibility improvements in winter and spring, however, lead to decreases in the probability of occurrence of fatal accidents in both counties, although these coefficients are not very precisely estimates. An improvement in visibility in Cook Counry by one mile leads to an estimated benefit of 9.45 million dollars as a result of reduction in traffic casualties.

OBJECTIVE FOUR: EVALUATION OF POLICY EFFECTS ON VISUAL RANGE

A detailed illustration of the application of the visibility value function to analysis of policy benefits was developed. Forecasting visibility policy effects requires comparing a without-policy or base-case scenario with one or more regulatory scenarios. The visibility value function was applied to four hypothetical or illustrative policy scenarios for electric utility pollution control relative to a base--case scenario. Benefits connected with these purely illustrative scenarios were estimated for the year 1990. Specifically, aggregate and per-household benefits were estimated for each eastern state and the eastern United States.

A method was needed which relates reductions in pollution emissions from the scenarios to visibility improvements. The relation between emissions and visibility was provided by results from research at Argonne National Laboratory.

Illustration of Method

Step A in the analysis of visibility regulation was to establish policy alternatives. Alternative policies produce different patterns of visibility improvement whose effects need to be evaluated in order to make a policy choice. Three such policies were considered. In addition to the policy scenarios a without-policy or base-case scenario was formulated. The base-case scenario is a judgement as to the most likely regulatory climate in the absence of a visibility policy. It provides the standard against which the benefits of the policy scenarios are measured.

Step B was to forecast emissions under the base-case and policy scenarios by type of emittor, season and amount of pollution. These forecasts depended in part on the technical requirements of pollution abatement. To an even greater extent the emissions forecasts depended upon forecasts of future levels of economic activity.

Step C was to forecast the spatial distribution of ambient air quality. The relationship between emissions and ambient air quality depends upon the way emissions are dispersed geographically and the chemical transformations that occur during dispersion. This step was performed for each of the scenarios by means of the Argonne long range transport model. [Rote, 1982a]

Step D was to measure the effects on visibility of ambient air quality resulting from each scenario. The solution to this problem, also supplied by Argonne [Rote, 1982b] provided a set of predictions as to the course of visual air quality on a state by state basis in the future.

Step E was to use the visibility value function to establish values associated with alternative pollution control strategies. Each scenario produced a set of improvements in visual range for each state in future years. The function estimated the value of these improvements to a state as the sum of the value of the local component and value of improvements in other parts of the region due to existence and option values. Non-local improvements are less valuable to the state depending upon their distance from the state. The value of visibility improvements is the sum of all local and non-local improvements for all states in a given year. The visibility value function evaluated improvements for each state in all years for each of the four policy scenarios.

Aggregation of Illustrative Scenario Benefits in the Eastern United States, 1990

Table 2 presents 1990 policy benefits for the three illustrative improvement scenarios. Total program benefits for the three illustrative scenarios in the year 1990 range from about two billion dollars (scenario 3) to about fifteen billion dollars (scenario 5).

New York, Pennsylvania, Ohio, Illinois, Michigan, and New Jersey are the six leading beneficiaries of scenarios 4 and 5 in 1990. New York, Pennsylvania and Ohio lead in scenario 3 as well. These six states account for between 50 and 60 percent of eastern benefits under all three scenarios. New York., Pennsylvania and Ohio receive between 35 and 45 percent of eastern benefits under all three scenarios. The pattern of benefits is a little different on a per-household basis. Still, it is the highly populated and industrialized Northern states where the highest values of improved visibility occur. While individual state rankings are somewhat sensitive to the specification of the endowment index and the aggregation pattern based upon contingent valuation, nevertheless the basic pattern is rather striking.

Estimates of the visibility valuation function are the best we have at this time, but are subject to considerable refinement and investigation of reliability. The aggregate benefits estimates have been presented only for purposes of illustrating aggregation methodology. Care should be exercised that the results not be used out of context. The policy scenarios are for various kinds of utility controls and are not to be taken as indicating that these policies are actually being contemplated or should be enacted. A major point in illustrating the aggregation method is to emphasize that there is no one

TABLE 2

Annual Household Benefits and Total State Benefits
Relative to Base Case, 1990

State	Scenario 3		Scenario 4		Scenario 5	
	State Benefits ($ millions)	Benefits per Household ($)	State Benefits ($ millions)	Benefits per Household ($)	State Benefits ($ millions)	Benefits per Household ($)
NY	397	58	1111	162	2394	350
PA	315	71	820	184	1725	386
OH	224	53	773	184	1516	360
VA	163	77	418	197	785	370
NJ	152	52	430	146	862	292
MD	150	84	388	216	756	421
NC	111	49	244	107	492	216
IN	107	51	359	171	714	339
WI	89	48	174	93	368	198
MI	78	21	421	116	904	249
MA	48	21	282	124	588	260
WV	39	59	109	163	219	328
KY	30	22	211	157	380	282
SC	30	26	126	110	217	190
CT	28	22	137	109	308	244
TN	24	14	244	142	427	249
GA	22	10	230	109	355	168
DC	20	70	56	192	107	371
FL	20	4	214	48	342	77
AL	11	8	110	79	176	126
DE	11	44	30	123	61	248
NH	8	21	72	197	114	311
MS	6	6	57	66	88	102
RI	6	14	33	87	72	187
VT	5	23	31	153	59	289
ME	4	10	49	113	73	167
Total	2,193		7,766		15,134	

unique value of increased visibility, but rather the benefits of a program affecting visibility depend on how much visibility is improved in different places, and on the numbers and characteristics of people in the places affected. It would defeat a major purpose of this study if the numbers in this study were applied out of context to other programs. The use of the results of this study should be to estimate differential improvements in visibility that would be brought about by a program and then to use the visibility function to obtain benefits in different states which would then be summed. The purpose of this study has been to develop operational tools. The tools can be applied for actual policy purposes, but they have not been so applied in this study. Further work is being undertaken to extend and refine the results of this report.

APPENDIX A: SURVEY INSTRUMENT

This Appendix contains the Contingent Valuation instrument used in the Eastern survey. It contains the modules discussed in detail in the main report. The same survey was used in all six cities, within some city-specific modifications, as on page 3.

Form# A- 174
Inter...

City ATLANTA

[Check One]--
Center City
Suburban
Rural

Did not copy

EASTERN U.S. RESIDENTS

the University of Chicago. We are
as part of a research study about
e are talking with a scientifically
dents, the viewpoint of your house-

Ia. Are you the male/female head of household?

YES______ (Go to statement at bottom of page)

NO______ (Ask Ib.)

Ib. Is the male or female head of household at home?

YES______ (Ask to speak with head of household. Start Over.)

NO______ (Thank respondent and terminate.)

Fine. I have a few questions that I would like to ask you. It will take about 20 minutes, and your answers will kept confidential.

FORM NUMBER A-174

ACTIVITY SHEET

GROUP 1

- ______ Walk to Work
- ______ Drive to Work
- ______ Eat Lunch Outdoors
- ______ Leave Place of Work for Lunch
- ______ Take a Vacation Day
- ______ Outdoor Work Around House
- ______ Employed in Outdoor Job

GROUP 2

- ______ Jogging/Running/Bicycling
- ______ Swimming/Sailing
- ______ Tennis(outdoor)/Golf
- ______ Outdoor Team Sports

GROUP 3

- ______ Sightseeing(Rura1 or Urban)
- ______ Photography (Outdoor)
- ______ Drive in the Country
- ______ Flying/Gliding/Hang Gliding

GROUP 4

- ______ Stroll in the Park
- ______ Walk the Dog
- ______ Sunbathe
- ______ Go to Outdoor Fair/Concert
- ______ Play Catch/Frisbee

GROUP 5

- ______ Indoor Tennis/Racketball/ Basketball/Volleyball
- ______ Work Out at the Gym
- ______ Bowling
- ______ Other Stenuous Indoor Activities

GROUP 6

- ______ Go to Shopping Mall
- ______ Go to Museum
- ______ Go to Movies
- ______ Other Indoor Activities Away From Home

Group 7

- ______ Stay at Home

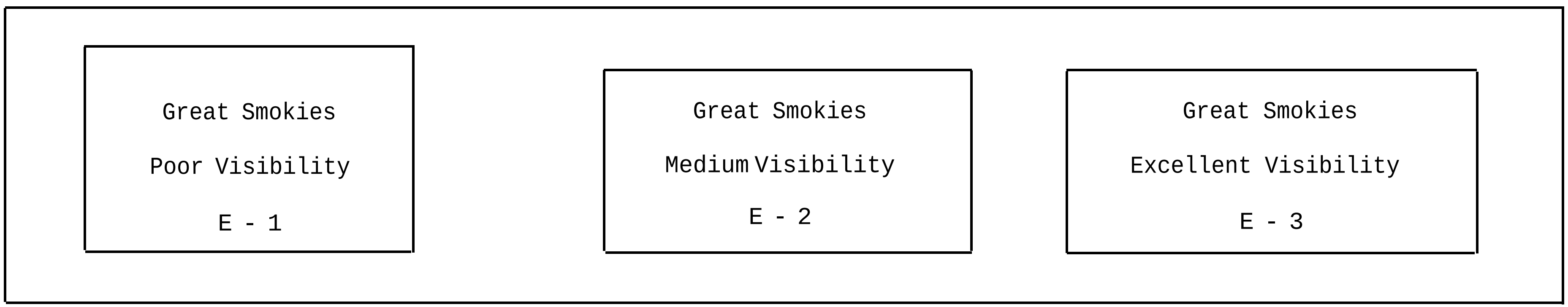
GROUP 8

- ______ Nature Study/Bird Watching
- ______ Fishing/Hunting
- ______ Hiking/Trail Riding
- ______ Camping/Backpacking
- ______ Attend College or Pro Ballgame
- ______ Sightseeing Outside Local Area
- ______ Visit Friends in East U.S.
- ______ Visit Friends in West U.S.
- ______ Visit State/National Park
- ______ Other Activities Away From Local Area

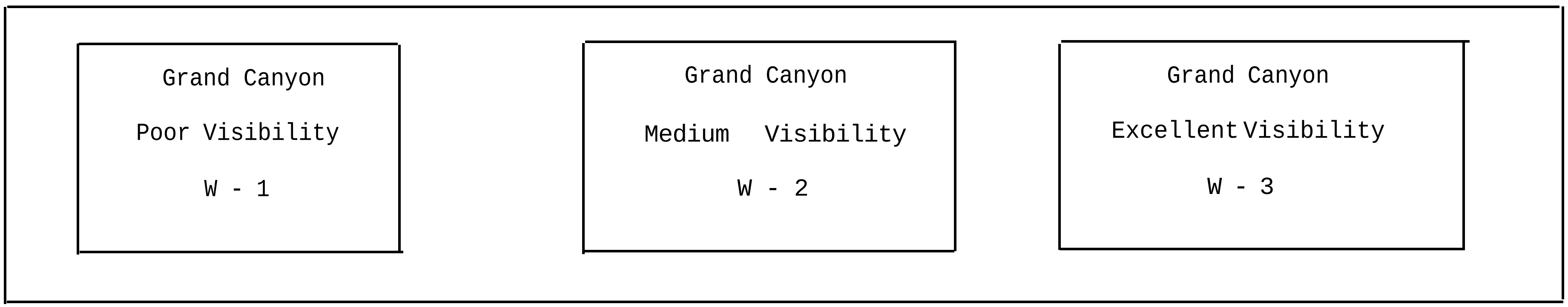
SKETCH OF
PHOTOGRAPH DISPLAY BOARD FOR
LOCAL VISIBILITY IN THE EAST

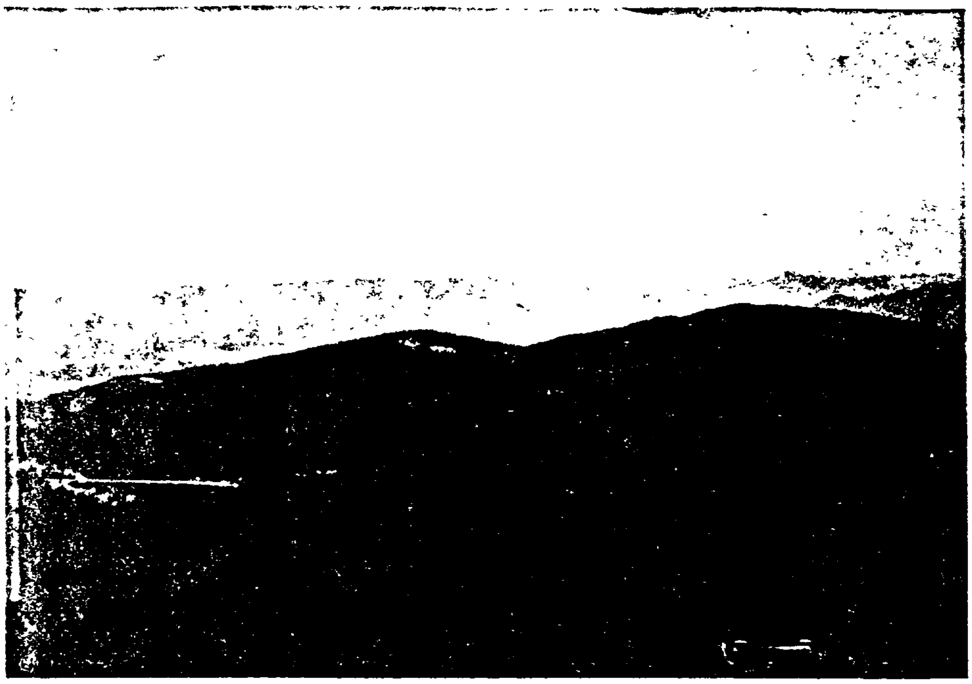
Apartments and Skyline Poor Visibility L - I - 1	Apartments and Skyline Medium Visibility L - I - 2	Apartments and Skyline Excellent Visibility L - I - 3
Outer Drive Poor Visibility L - II - 1	Outer Drive Medium Visibility L - II - 2	Outer Drive Excellent Visibility L - II - 3
Urban Shoreline from High Floor Poor Visibility L - III - 1	Urban Shoreline from High Floor Medium Visibility L - III - 1	Urban Shoreline from High Floor Excellent Visibility L - III - 3

SKETCH OF
PHOTOGRAPH DISPLAY BOARD FOR
VISIBILITY IN THE EASTERN REGION AS A WHOLE



SKETCH OF
PHOTOGRAPH DISPLAY BOARD FOR
VISIBILITY IN THE WEST

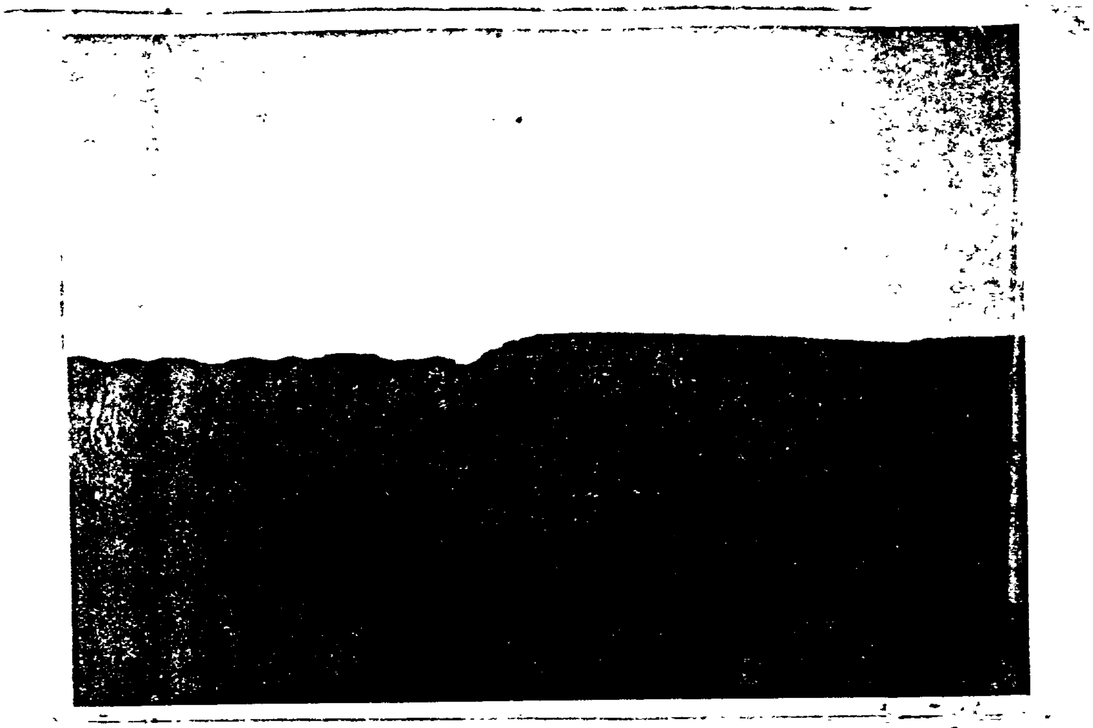




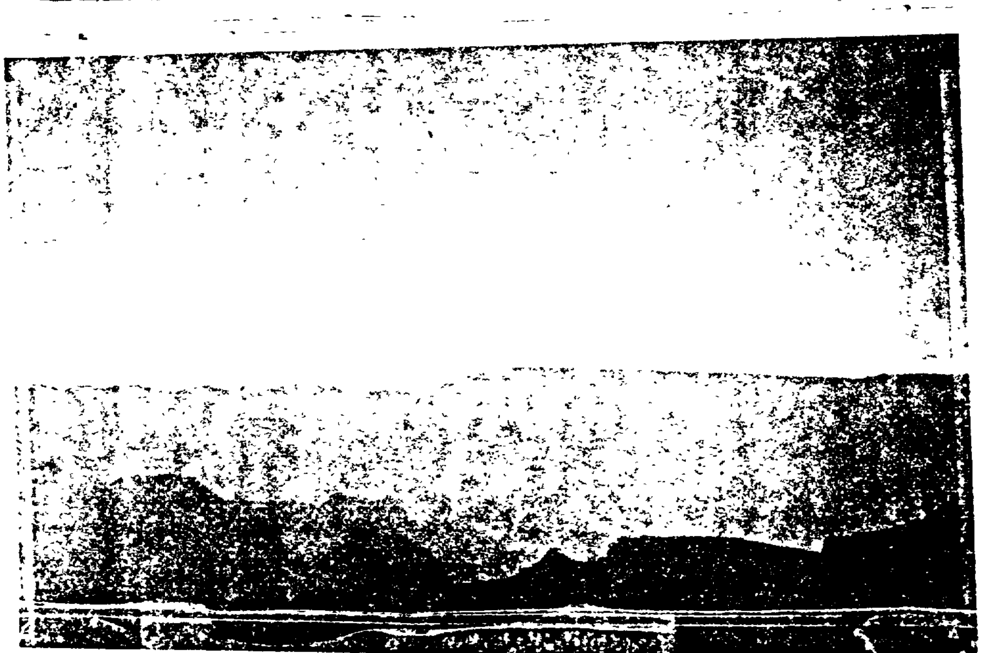
E-3

E-2

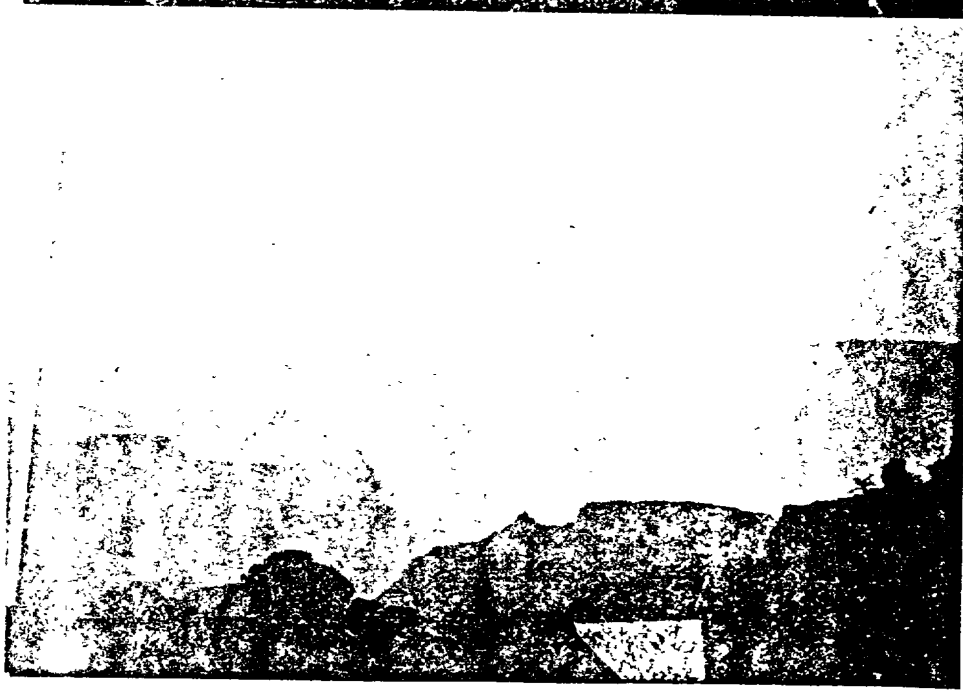
E-1



W-3



W-2



W-1